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Ecologically Inspired Metrics for Rare Earth Element Critical Material Systems

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by

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Sustainable Systems

Golisano Institute of Sustainability

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We, the undersigned members of the thesis committee, certify that we have advised and/or supervised the candidate on the work described in this thesis. We further certify that we have reviewed the thesis manuscript and approve it as partial fulfillment of the requirements of the degree of Master of Science in Sustainability.

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ABSTRACT

Greenhouse gas emission reduction targets have increased demand for clean energy technologies, and the growth required for these technologies has led to concern over material availability and criticality. Critical materials are defined as having risks associated with them such as supply gaps or price volatility. Existing metrics for criticality determination are narrowly focused on physical scarcity of single materials, whereas many critical materials are byproducts of large, complex, interconnected material systems. Industrial ecology borrows methods from ecology to study complex material and energy flows, which can be used for a systems-perspective analysis. In this work, critical rare earth material systems are likened to food webs and analyzed using ecological network metrics and metrics borrowed from network analysis. This study considers food web metrics—partner diversity, connectance, specialization asymmetry, vulnerability, extinction slope, niche overlap, weighted betweenness, normalized degree, interaction push-pull, cluster coefficient, Shannon's diversity, interaction evenness, and d'—best suited for describing systemic criticality in metal or mineral use systems. These metrics were applied to 10 rare earth elements and their end uses for China, Japan, and the United States from 1995-2007 as a case study to determine if ecologically inspired metrics could provide improved criticality assessment. Metrics address three system levels: 1) network, 2) group, and 3) individual elements/products. It was determined that some metrics highlight instances where rare earth systems are becoming more specialized making them vulnerable to supply risks. Application of ecological network metrics to material systems has advantages for criticality assessments, and future work should consider additional systems and the interactions between the various metrics to better understand these systems and lessons available from a systems-perspective.

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1. INTRODUCTION

Fossil fuel availability has been a major concern of society for decades, but these fears have shifted to include minerals and metals, as their usage has increased nearly three-fold since 1900 (Erdmann and Graedel 2011). Most recently, concerns have shifted specifically toward materials utilized by emerging clean energy technologies, or those important for sustaining society without the use of fossil fuels or significant increases in greenhouse gas emissions (Erdmann and Graedel 2011, Gunn 2014). Non-fossil fuel materials for which availability fears arise are typically termed "critical," and sometimes referred to by governments as strategic materials or strategic minerals (U.S. Department of Defense 2013). Studies surrounding these "critical materials" have increased dramatically in recent years (Speirs, Houari, and Gross 2013). Examining critical materials is important for the sustainability of our modern society, not only for technological advancement, but also for the deployment of clean energy technologies necessary for reducing anthropomorphic greenhouse gas emissions and climate change mitigation. By determining what materials are at risk for limited availability near- or long-term, strategies to mitigate issues related to the specific materials can be employed so a sustainable future can be realized.

1.1. Critical Materials

Criticality is a designation given to materials that are not only essential for the function of modern technologies, but also have risks associated with obtaining them (supply, environmental, and/or social). These materials are sometimes referred to by governments as strategic materials or strategic minerals (U.S. Department of Defense 2013, 2015). Critical materials have the potential to disrupt production for firms, reduce energy independence for governments, and are often subject to price volatility. When it comes to material criticality, there are three major questions: 1) How do we determine material criticality?, 2) If a material is critical, what can we do to avoid the consequences?, and 3) Is it possible to predict or prevent material criticality? Thus far, significant research has been done on how to determine criticality and how to measure the relative degree of criticality, but is not prescriptive in how we can avoid consequences, nor does it address prediction or prevention (Graedel and Reck 2015, Graedel et al. 2012, Glöser et al. 2015, Goe and Gaustad 2014, Rosenau-Tornow et al. 2009). Substantial efforts have been put forth in discussing and developing technologies for mitigating criticality including recycling development and new mine exploration, especially in the case of rare earth elements (Rademaker, Kleijn, and Yang 2013, 2014, U.S. Department of Energy 2011, U.S. Department of Defense 2015). Despite these efforts, most criticality work does not account for temporal aspects, historical trends, nor system-dynamics.

Traditionally, critical materials are determined by evaluating *supply risks* and *vulnerability to supply risks* in a two-axis "criticality space" (National Research Council 2008, Erdmann and Graedel 2011). Supply risks are related to physical interruptions in the form of unbalanced markets, supply chain interruptions, and government involvement, all of which can cause price increases and/or physical scarcities. Vulnerability to these supply risks varies for the system of interest and perspective (country, government, or firm), thus criticality is determined on a case-by-case basis. Recently developed methodologies for criticality determination expanded the two-axis approach to include environmental criterion (Graedel et al. 2012, Goe and Gaustad 2014).

Understanding criticality is inherently complex due to the number of factors involved, inadequate data, and uncertainty in supply/demand projection (Graedel et al. 2012, Glöser et al. 2015). The multi-faceted nature of criticality assessment means that it relies on several different metrics, which proves challenging for thoroughly reviewing all material systems, some of which may be lacking data. Despite being multi-faceted, criticality assessments are typically narrowly focused with single-score metrics largely based on physical scarcity (Goe and Gaustad 2014). Criticality determination is important for firms and governments because it can spark early efforts to alleviate consequences of criticality.

Determining which materials are critical varies greatly based on the scope. Scope can depend on the data time-frame (one year or several years), criticality time-frame (short-term vs. long-term), institution-level (government, firm, global), and materials or elements considered (number of elements or which elements are considered). This variation requires that criticality methods and metrics be versatile and widely applicable, which can be limited significantly by data availability. Not only do the methods need to be flexible, but they must be reflective of the systems they are evaluating.

Currently, criticality studies focus severely on supply-side metrics. Most studies attempt to incorporate demand, but the missing piece is how the demand interacts with the supply and vice-versa. This is precisely what ecologists study when they examine plant-pollinator or consumer-resource networks. Material use systems that criticality methods aim to study are complex systems of supply and demand interactions, therefore, the methodologies and tools used to study them should reflect these features.

Because much of criticality work is driven by physical scarcity of the material, these materials become important for the technosphere, much like a key or service-provider species is important in an ecological system or food web. Such key species become a target for conservation or preservation and ecologists use network methods for determining information about the underlying structure of the system to identify areas of interest (Tylianakis et al. 2010).

Given this analogy, and to overcome current criticality limitations, this work seeks to determine: 1) what information can we gain about material systems using ecological and network analysis metrics? and 2) are there specific network analysis metrics that are practical for criticality?

1.2. Literature Review and Background

In this section, critical material evaluation studies and current limitations of those studies are outlined. This is followed by a review of potential ENA applications for critical material systems and previous ecological network analysis (ENA) applications in industrial ecology.

1.2.1. Critical Material Evaluation

In criticality studies, materials, mainly elements, are evaluated using supply risk and importance (Graedel and Reck 2015). Various metrics related to each element are aggregated to reflect supply risk or importance to give a final value. These values are compared to one another to give an overall relative criticality ranking. The elements with the highest rankings in both categories are considered critical. This designation is important so that adequate measures can be taken to reduce or avoid associated consequences.

Critical raw material studies have been conducted since the 1970s and 80s, and much like recent studies, focused on supply risks such as reliance on imports, co- or by-production, and concentration of production in unstable countries, rather than geological scarcity (Buijs, Sievers, and Espinoza 2012, Gunn 2014).

The first modern study defining criticality and suggesting metrics for criticality determination was conducted by the US National Research Council (NRC) (National Research Council 2008). The NRC method consisted of two criteria: 1) supply risk and 2) impact of supply disruption. Figure 1 shows how each of the 11 metals or metal groups were ranked using these two criteria and plotted on a criticality matrix. Metals or groups that are most critical fall under region 1, followed by 2 and 3, and region 4 being least critical, comparatively. Rhodium was most critical in this study, while copper was deemed least critical, and it was noted that this study was to demonstrate the concept of criticality determination.

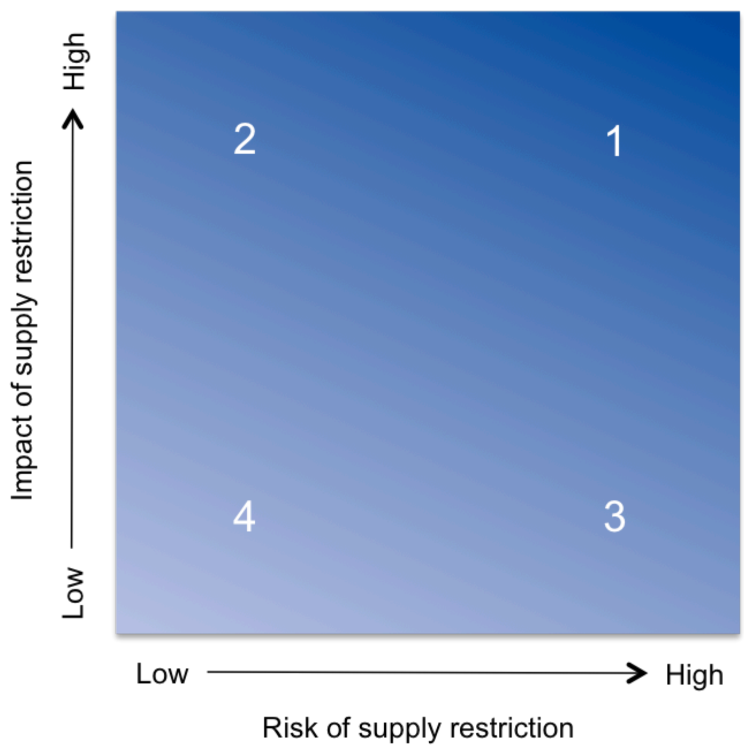


Figure 1. Example of the criticality matrix developed by the US National Research Council and altered by Graedel et al.
(National Research Council 2008, Graedel et al. 2012)

Similarly, the European Commission (EC) conducted a criticality study for the European Union (EU) evaluating 41 metals and minerals using two-axis criteria: 1) economic importance and 2) supply risk – poor governance (European Commision 2014). Each axis accounted for multiple factors and if both exceeded an arbitrary threshold, then the material was deemed critical. In the most recent evaluation, economic importance was determined using end use sectors' market percentage and gross value added with respect to the EU gross domestic product, and supply risk was based on substitutability, recycling rates, and concentration of countries for factoring unstable governments (European Commision 2014).

The U.S. Department of Energy (US DOE) also utilized the two-dimension approach to criticality; however, rather than vulnerability to supply risk, it considered importance to clean energy (U.S. Department of Energy 2011). The most notable differences of this study are the consideration of two time scales: 1) short-term (0-5 years) and 2) medium-term (5-15 years) and designation of three regions: 1) critical, 2) near-critical, and 3) not critical. Importance to clean energy factors included clean energy demand and substitutability, while supply risk factors were basic availability, competing technology demand, political, regulatory, and social factors, codependence on other markets, and producer diversity. Sixteen elements were considered. While those most critical were rare earth elements: dysprosium, europium, and terbium in the short-term and dysprosium in the medium-term. Several elements were labeled as not critical (U.S. Department of Energy 2011).

Expanding on the two-axis methodologies, Graedel and colleagues proposed a three-axis methodology considering: 1) supply risk, 2) vulnerability to supply risk, and 3) environmental implications (Graedel et al. 2012). Despite incorporating time-scales, Graedel et al. admit that their methodology is merely a "snapshot" and that future studies should better consider "temporal aspects of metal criticality" (Graedel et al. 2012). Their method is also presented with significant flexibility with respect to scope, but it requires a considerable amount of data, some of which may not be available for individual elements of element groups such as platinum group metals or rare earth elements.

Goe and Gaustad (2014) developed a methodology for criticality relative to sustainability (social, environmental, and economic factors considered) and applied the methodology to elements utilized by solar photovoltaic technologies. They point out that much of the prior approaches were narrowly focused on physical availability and some previous studies did not consider interdependencies (Goe and Gaustad 2014).

These major studies and a few others were reviewed by Erdmann and Graedel (2011), Buijs et al. (2011), and Speirs et al. (2013) who pointed out that the variations in methodology proved difficult for selecting one or two materials as most critical (Buijs, Sievers, and Espinoza 2012, Erdmann and Graedel 2011, Morley and Eatherley 2008). Additionally, these reviews served to highlight that criticality assessment methodology is still developing and results are not universally applicable.

Although methodologies have significantly improved with respect to being comprehensive and transparent, incumbent methodologies still aggregate static metrics and indices and are narrowly focused on the supply-side, losing sight of the system and individual factors. Many criticality assessments utilize linear summation or result in a single-score ultimately determining whether an element is critical or not. This approach conceals specific factors crucial for making policy decisions regarding that material. For example, a metal that has no substitutes, but scores fairly low in terms of most factors, would not be considered critical although it is vulnerable to supply risks if one or more factors change. This method also assumes that each factor should be weighted equally. Knowing which factors are contributing to a material's criticality designation and which factors are most important to the practitioner is key to implementing appropriate mitigation strategies (e.g. recycling development, stockpiling, opening of new mines, substitution exploration) to avoid consequences (e.g. price spikes, physical scarcity). By focusing on physical scarcity and narrow time-scales, criticality practitioners lose sight of the complexities and changing trends in demand.

Systems consideration is a significantly overlooked component in criticality studies because most of the elements evaluated are actually part of complex material use systems - produced as byproducts or coproduced and utilized by an array of technologies. Graedel et al. (2015) point out that in addition to being used in small quantities for specialized applications (recycling challenge) and having little or no effective substitutes, the majority of metals and metalloids considered to be critical are obtained via byproduction, which necessitates using a systems perspective (Bustamante and Gaustad 2014).

Future criticality studies should better address temporal aspects, provide results that are prescriptive rather than relative, and take a systems perspective. Current methods are unable to predict and reflect only a snapshot in time due to the static nature of the data. Incumbent methods quantify and sum, or aggregate, various factors that contribute to criticality. This makes it unclear which factors contribute to an element's criticality, so the results are not necessarily intuitive to a government entity or firm. Stakeholders may or may not be concerned depending on the reason an element is critical, and because results are aggregate or the reason for criticality is not clear, it is difficult for them to discern their level of concern. Lastly, it is difficult to discern how the system will fair without the material based on current studies, and a systems perspective is key to understanding how other markets will be affected by supply disruptions or price spikes.

Network or ecological network analysis is proposed as a solution to overcome limitations of criticality studies. Network analysis is used to study the underlying structure and relationships of systems to better guard against perturbations and understand how systems evolve (Barabasi 2002). This provides an opportunity to addresses criticality by focusing on change over time through a systems-perspective (bridging supply and demand) to minimize disruptions, rather than focusing on scoring elements against one another. This work utilizes an industrial ecology approach by applying ecological concepts to the industrial system of material use.

1.2.2. Ecological Network and Network Analysis

This work proposes utilizing an industrial ecology analog via ecological food webs and ultimately network analysis to overcome the current limitations of criticality studies. Industrial ecology (IE) is the term used to describe using ecological analogs for studying material and energy flows from a systems-perspective (Graedel and Allenby 2010). Here, potential benefits of using ecological network and network analysis for material use systems are described.

Ecological network analysis, in particular, is used to study food webs and mutualistic (plant-pollinator) or antagonistic relationships (predator-prey) to better understand system stability, as well as which species are important for the function of the system. Specifically, it has been used to understand what features of a food web contribute to robustness toward species extinctions (Dunne, Williams, and Martinez 2002b). Significant research has been done to understand how to determine specialized species (those that rely on one or few other species) and what impact they have on the entire system (Blüthgen, Menzel, and Blüthgen 2006, Bluthgen et al. 2007, Blüthgen et al. 2008, Dormann 2011). Robustness to extinction is important for critical material systems because it is of interest to understand how the market will fair if an element is removed. Specialization is important as well because it can aid in understanding which elements are most important for specific products or vice-versa.

Another potentially useful aspect of ecological networks for criticality is understanding diversity and its relationship with stability. The concept of diversity has been proposed as a way to overcome criticism of industrial ecology lacking connection to its source science and has since been applied in studies surrounding the performance of industrial parks, household electronics, and energy supply (Wells and Darby 2006, Wright et al. 2009, Ryen et al. 2014, Chuang and Ma 2013, Layton, Bras, and Weissburg 2015). For applications of diversity and stability related to networks, the relationship or underlying mechanism, and even the existence of an underlying mechanism, is widely debated, as are the various metrics utilized; therefore, its usefulness for critical material systems requires further study (Pielou 1975, McDonald and Dimmick 2003, McCann 2000).

In addition to these topics, network analysis and ecological networks employ various metrics to describe their underlying structures. Underlying structure dictates much of the network analysis and is the basis for the majority of network studies. Defining whether a network is small-world, scale-free, etc. dictates how networks grow and respond to perturbations (Barabási and Frangos 2014, Albert and Barabási 2002). Ecologists found that food webs behaved like small world networks, but they did not meet the fundamental requirements (Dunne, Williams, and Martinez 2002a). Food web analysis has its own set of structural metrics that include things like species richness (number of species), connectance (number of realized links), linkage density (links per species), generality (prey per predator), and vulnerability (predator per prey) (Dormann et al. 2009).

In addition to diversity and structure, there is an even larger body of work and numerous opportunities at the cross-section of network analysis and ecology that can be translated to material systems that is beyond the scope of this work (Blüthgen 2010). Furthermore, it cannot be assumed that ecological or network concepts will translate exactly to the material system, so in order to determine if ecological network measures and concepts translate to material criticality, this thesis explores a material network that was developed and studied based on the rare earth element system (Isenmann 2003).

1.2.3. Previous Studies in Industrial Ecology

Ecological food web metrics have been applied previously in industrial ecology to industrial parks and household electronics (Hardy and Graedel 2002, Wright et al. 2009, Ryen et al. 2014, Layton, Bras, and Weissburg 2015). Hardy and Graedel (2002) demonstrated the use of food-web analysis for industrial ecosystems and evaluated the connectance of industrial parks, and Wright et al. expanded on this work by evaluating an array of ecological metrics for a specific industrial park. Layton expanded on the work of both of these studies by incorporating additional food web metrics and making suggestions about the organization of the data. These studies used the metrics as a benchmarking tool for evaluating the performance of industrial parks. In these studies, if the industrial park could be shown to be as interconnected as an ecosystem, or to cycle nutrients as well, then it might be considered sustainable. Ryen et al. (2014) related household electronics to a community and used diversity metrics to evaluate how the community diversity changed over time and recommended converging functionality for emerging products. The major outcome of their work was that individual functional diversity increased over time.

This work contributes to the growing field of industrial ecology by applying ecological network metrics to a material web providing a systems perspective for criticality. It explores a layered approach, allowing for an in-depth analysis of the system and interdependencies while examining ecological metrics that are best suited for this type of analysis. An ecological network approach allows the critical material system and elements to be studied as an ecologist might study a species for conservation or preservation efforts. In these instances, system stability, diversity, robustness, and other food web properties dictated by the underlying structure and interactions are key for introducing appropriate conservation tactics. The same is true of critical materials, without a systems perspective, systems response and policy actions and implications cannot be fully understood.

In the following sections, the methodology and approach to material webs are described in detail, including ecological metrics considered in this work and their meanings. Then, comprehensive results from applying these metrics to rare earth element material webs are presented and assessed for trends and ultimate usefulness to criticality characterization. Finally, conclusions for this industrial ecology approach are presented and future work is discussed.

2. METHODOLIGICAL APPROACH

In general, the methodology for this work was to first select a case-study focused on a universal critical material system by collecting data related to flows of the system. A system that is already considered critical was selected for cross-referencing new metrics and previous criticality findings. Then, data related to the mass flows of the elements was collected to develop a quantitative material web. Using the quantitative material web, ecological network metrics were analyzed at three different levels: 1) network, 2) group, and 3) individual. Finally, metric descriptions, prior applications, and correlation analysis were used to determine which, if any, metrics are redundant for the material web or not applicable for material criticality studies.

2.1. Rare Earth Elements Case-Study

Rare earth elements (REE) were chosen as the representative critical material system. REE or rare earths (RE) consist of yttrium, scandium, and the lanthanide series on the periodic table. Five REE: dysprosium, europium, terbium, yttrium, and neodymium; have been deemed critical by several studies including the U.S. Department of Energy (U.S. Department of Energy 2011, European Commission 2014). The U.S. Department of Defense has cited several RE as "shortfalls," where U.S. resources available for these elements are not expected to meet demands (U.S. Department of Defense 2013, 2015).

REE are important for clean energy technologies (wind turbines, electric vehicle batteries, lighting phosphors), have very few substitutes, little or no recycling (recycling rates are <1%), and the majority are produced in China (Reck and Graedel 2012, Graedel et al. 2013, U.S. Department of Energy 2011). They are found in low concentrations and widely dispersed geographically, resulting in energy and resource intensive recovery processes (Nuss and Eckelman 2014, Sprecher et al. 2014, Tharumarajah and Koltun 2011, Althaus et al. 2007, Zaimes et al. 2014, Bustamante et al. 2016).

Despite their criticality designation, these materials are continually utilized in new and emerging products. For example, nine REE are needed for the modern iPhone (color screen, glass polishing, phone circuitry, speakers and vibration unit), whereas previous cell phones utilized only three or four REE (Greene 2012). Due to their coproduction, similar properties, and lack of individual data, REE are often considered in aggregate for criticality studies (European Commission 2014, National Research Council 2008). The complexity of the system, increasing number of utilizing products, and criticality designation make the RE material system the ideal case-study for a network analysis.

Material flow analysis data for rare earths was used to develop bipartite networks for three countries over 12 years and evaluated using bipartite metrics in R from the Bipartite package (R Core Team 2015, Dormann, Gruber, and Fruend 2008). Metrics were selected and studied to understand the relationships between various metrics for a material system and evaluated for their usefulness with respect to critical material systems.

2.2. Data Collection

Quantitative data was collected from material flow analyses and reports on REE for three Countries (China, Japan, and United States) for the years 1995-2007 (Du and Graedel 2013, Nassar, Du, and Graedel 2015). The data consisted of ten rare earth elements and an "others" category: 1) lanthanum (La), 2) cerium (Ce), 3) praseodymium (Pr), 4) neodymium (Nd), 5) samarium (Sm), 6) europium (Eu), 7) dysprosium (Dy), 8) gadolinium (Gd), 9) terbium (Tb), and 10) yttrium (Y). Information about the uses of rare earths is summarized in Table 1. It also included ten products associated with the use of rare earths: 1) magnets or permanent magnets, 2) battery alloys, 3) metallurgical alloys (excluding battery alloys), 4) automobile catalysts (auto catalysts), 5) fluid cracking catalysts (FCC), 6) polishing powders, 7) glass additives, 8) phosphors, 9) ceramics, and 10) other. These "products" are often incorporated into end uses or final products, which are summarized in Table 2. For additional information regarding the rare earth data see Du and Graedel (2013), Nassar et al. (2015), Goonan (2011), and U.S. Geological Survey (1994-2012, 1996-2015). The connections between the products and elements, measured in mass of the element used by the product, was used to develop the material network.

Table 1. Elements used in the data analysis and their common applications or products

Element	*Symbol*	*Applications**
Yttrium	Y	Alloys; red phosphors for flat screens and lighting (liquid crystal display (LCD), light-emitting diodes (LEDs)); camera lenses (as a glass additive for heat and shock resistance); microwaves; and radar
Lanthanum	La	Alloys; battery alloys (nickel-metal-hydride (NiMH) as LaNiH); auto catalysts (catalytic converters for internal combustion vehicles); fluid cracking catalyst (FCC); glass additive (improves optical properties); ceramic superconductors; and polishing powder
Cerium	Ce	Polishing powder; fluid cracking catalyst (FCC); automotive catalytic converters; glass additive (reduces rate of discoloration); alloy (primarily misch metal used as flint in lighters and torches); ceramic coatings; cathodes for solid-oxide fuel cells; capacitors; semi-conductors; and more
Praseodymium	Pr	Alloy (misch metal, magnesium for aircraft industry); glass additive (pigmenting, blocks infrared radiation); auto catalyst (catalytic converter); batteries; magnets; ceramics; and polishing powder
Neodymium	Nd	Permanent magnets (neodymium-iron-boron magnets (NdFeB), see magnet applications below); lasers; and auto catalysts (catalytic converters)
Samarium	Sm	Magnets (samarium-cobalt (SmCo)); calibration material for spectrophotometer wavelengths; reducing reagent; and defense applications (neutron absorber for nuclear reactors, lasers, capacitors)
Europium	Eu	Primarily used as a phosphor (for blue coloring in flat screen monitors, televisions, lighting, etc.); and defense applications (nuclear control rods, lasers)
Gadolinium	Gd	Magnets and magnet alloys (magnetic cooling, magnetic resonance imaging (MRI machines)); red phosphors; nuclear reactor shielding; and defense applications (computer storage devices, semiconductors and electron tubes, magnetic and optical recording devices)
Terbium	Tb	Solid-oxide fuel cells; green phosphors; luminescent materials; and lasers (defense application)
Dysprosium	Dy	Magnets (neodymium-iron-boron (NdFeB) magnet additive); and defense applications (nuclear control rods, ceramics for electronics)
*Others**: (Scandium, Promethium, Holmium, Erbium, Thulium, Ytterbium, and Lutetium)*	Sc	Alloys (aluminum); metal halide light bulbs; petrochemical (oil refining); and aircraft parts and equipment (defense application)
	Pm	Used almost exclusively in research, not found in nature, used for producing X-rays
	Ho	Nuclear reactors; magnetic flux concentrator; lasers (medical and dental applications (safe to the human eye)); and semiconductors and electron tubes (defense application)
	Er	Glass additives (photographic filter, safety glasses (for welders and glass blowers)); medical and dental lasers, production of nuclear fuel rods; alloys; and energy wires and cables (defense application)
	Tm	Lasers; radar systems; remote sensing; and semiconductors and electron tubes (defense application)
	Yb	Strengthening of steel; electronic devices; very few commercial applications; energy wires and cables (defense application)
	Lu	Petrochemical (oil refining); energy wires and cables (defense application)

*Compiled from various sources (Voncken 2016, Peiró, Méndez, and Ayres 2013, Gschneidner 1981, U.S. Department of Defense 2013).
**Use of these materials is very low and flows largely unknown (Du and Graedel 2013).

Table 2. End products for products included in the data analysis

Products	*End-Products**
Magnets	Electrical and electronic devices (speakers, computer hard disk drives), electric vehicles, wind turbines, magnetic resonance imaging (MRI machines), magnetic cooling
Battery Alloys	Electrical and electronic devices, electric vehicles
Metallurgy (except batteries)	Alloys, steel
Auto Catalysts	Internal combustion engines vehicles
Fluid Cracking Catalysts (FCC)	Petrochemical production, catalysts for breaking up long hydrocarbon chains
Polishing Powders (abrasives)	Various glass products and industries
Glass Additives	Various glass products (e.g. camera lenses)
Phosphors	Liquid crystal displays (LCD), plasma panels, lighting
Ceramics	Ceramic products (ceramic tiles, electronic ceramics)
Others	Likely to include lasers and superconductors

*Compiled from various sources (Voncken 2016, Peiró, Méndez, and Ayres 2013, Gschneidner 1981, U.S. Department of Defense 2013, Yoldjian 1985).

2.3. Networks and Metric Components

In network analysis, the individuals interacting are *nodes* and the connections between the nodes are *links* and in ecological networks, the individuals are typically species with various interaction types making up the links (Albert and Barabási 2002).

Ecological network analysis comes from network analysis which is based on graph theory. Graph theory is the study of graphs which model pairwise relationships between objects. In graph theory, like network analysis, the objects are the *nodes* and the interactions are *edges*. For example, a network or graph of movies illustrates the connections between the movies, the connection, or edge, can represent shared actors or shared producers. Each movie, or node, is assigned a number, and if paired, those movies share an actor.

In this work, the individuals, or nodes, will be referred to as products or elements and the links refer to the mass of the element utilized by the product. This is a directional relationship such that the products are "consuming" the elements. Collected data was used to construct bipartite networks for the rare earth system. Bipartite networks were utilized as they are common for studying two distinct groups that are interacting. In an ecological setting, these are typically mutualistic or predator-prey relationships, and in social network analysis are commonly represented using actor-movie relationships (Albert and Barabási 2002). The material flow analysis data described in the previous section was used to generate a bipartite matrix for each country and year for conducting ecological network analysis.

Bipartite networks are applicable for this work because the data follows the requirements outlined by graph theory. In graph theory, bipartite graphs have no odd cycles, in other words, no cycle can have an odd number of edges (Marcus 2008). In bipartite graphs, the network edges must contain one of each node type. If it has node types m and n, each edge must connect to an m and an n (Junker and Schreiber 2008). If an edge connects n to n or m to m, the graph is not bipartite. In a cycle, the path begins and ends at the same node without repeating nodes in between (Fournier 2013). The number of edges dictates whether the cycle is even or odd, Figure 2.

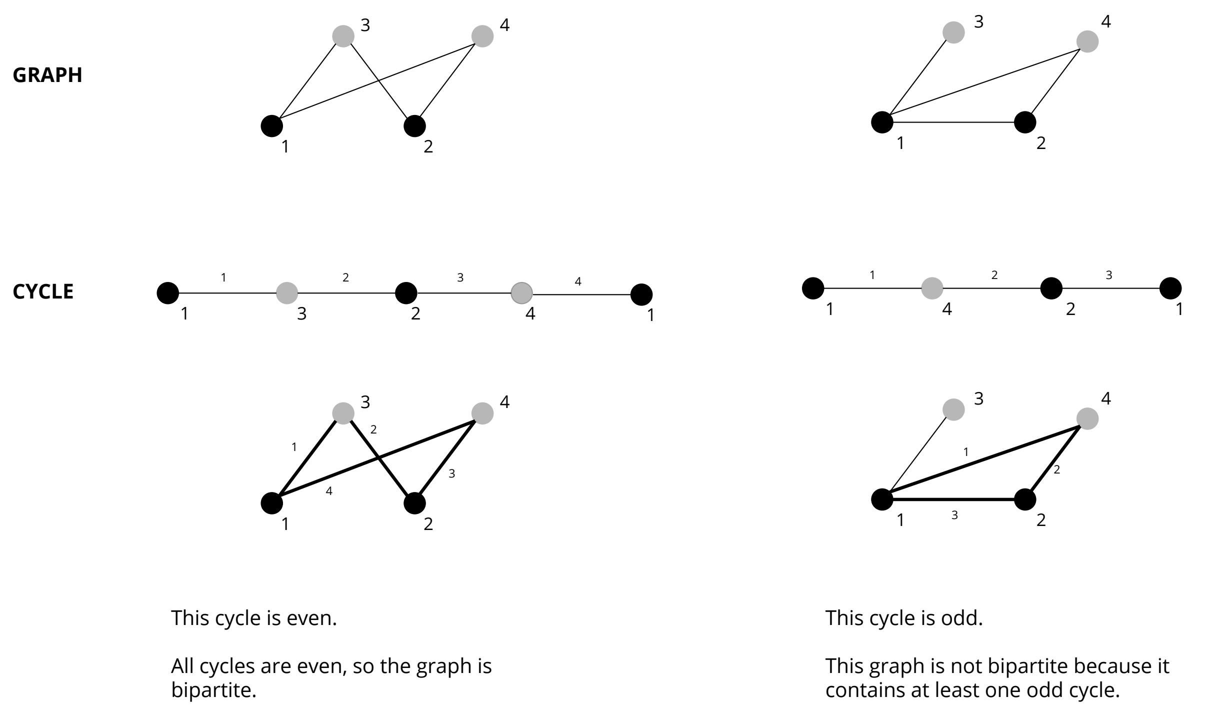


Figure 2. Example of odd and even cycles demonstrating proof that a graph is bipartite.
On the left, the cycle starts and ends at node 1 and does not repeat nodes in between. Its number of edges is equal to 4, so it is even. It is not possible to draw an odd cycle for this graph. On the right, the cycle starts and ends at node 1, but its path length is 3, so it is odd and not a bipartite.

The rare earth element system here is considered bipartite because the relationship connecting the elements and products is the mass of that element used in the product. We cannot say that a mass of one of the products is used in another one of the products, nor can we say that an element is used within another element. There are other relationships that exist between the elements such as coproduction (being produced from the same ore) and substitution (being substituted for one another in a product or application), but, the coproduction relationship especially, requires another node (e.g. a mine where elements are coproduced or a product where elements are substituted) or level of nodes. The addition of mine/source nodes would add additional levels to the bipartite network which would generate a multipartite, or tripartite (having three levels) specifically. As long as the nodes in each level are not interacting with one another, it is considered a k-partite network.

It is important to note that bipartite networks can be translated into two single-mode networks where each group has its own network and connections are drawn between two individuals that have a common link (two actors are connected if they worked on the same movie or two movies are connected if they have a common actor).

Figure 3 shows a sample material web. The main similarity between the material web and a food web is that species are being consumed by or interacting with other species. For the material web, data is limited for each element-product pair and for the food web, data is limited by observations. In both webs, species can be measured by magnitude. However, magnitude in the ecological case is typically observed/measured by population or biomass and in the material web, by mass or embodied energy (Magurran 1988). This system is an expansion to the bipartite webs analyzed in this study, but it highlights the potential extensions of this methodology to consumer products and a broader material web.

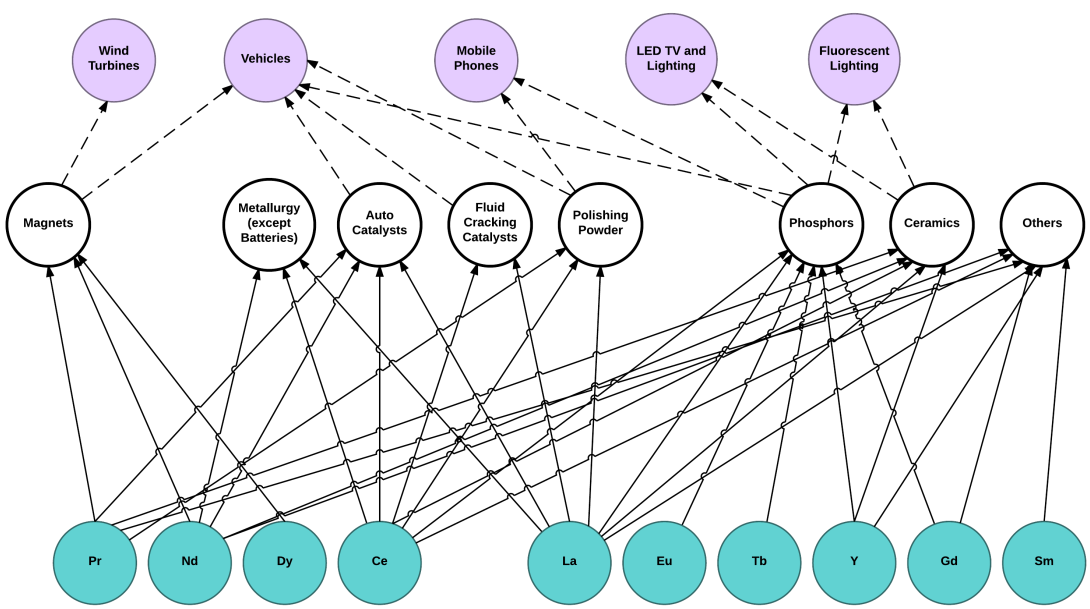


Figure 3. Sample material web for rare earths, end uses, and subsequent products for the U.S. in 2007 (Du and Graedel 2013, Peiró, Méndez, and Ayres 2013)

Bipartite metrics were analyzed for the rare earth material webs. For criticality, it is important that the most useful and non-redundant metrics are utilized. Correlation coefficients and cluster analysis were employed to determine which of the bipartite metrics listed below were related.

These results were compared to metric descriptions so that redundant metrics could be eliminated from final analysis and patterns in critical material systems could be identified.

2.4. Ecological Bipartite Metrics

Ecological bipartite systems are different from typical food webs. Although this work focuses on a bipartite material web, the material web shown previously, Figure 3, is not a bipartite, but representative of a trophic food web. Trophic food webs are organized by feeding levels or position in a food chain (Krebs, Boutin, and Boonstra 2001). In the bipartite web, two different species groups are interacting and make up the sides of the analysis matrix. Because one species type might be more numerous than the other, bipartite do not always form a square matrix. However, for a typical food web, the matrix is always square and all species are included in the sides of the matrix. This distinction, illustrated in Figure 4, is important and dictates much of the metric calculations.

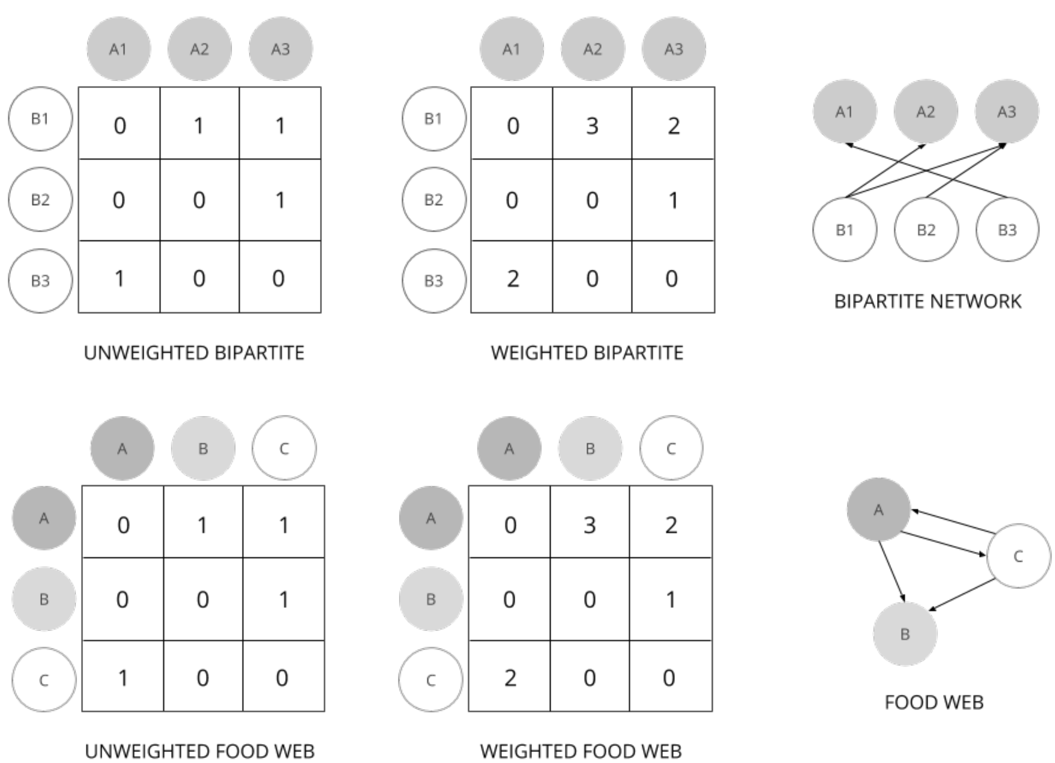


Figure 4. Bipartite and food web matrix with graph comparison

The full array of available bipartite metrics, listed in the following sub-sections, was analyzed for the material system. Simplified descriptions for these metrics are available in the Bipartite manual and publications (Dormann, Gruber, and Fruend 2008, Dormann et al. 2009, Dormann 2011). Additional details about metrics deemed appropriate are presented in the following sections and discussed further in the results.

For each level, a table is included for each metric that summarizes seven key features (as available): 1) name of metric, 2) ecological application and examples from ecology, 3) industrial ecology uses, 4) network analysis applications and samples, 5) calculation, 6) maximum or minimum values, and 7) references provided throughout. Metrics are followed by short discussions further describing information in the table, where necessary, and providing commentary on the usefulness or applicability to material systems.

Symbols and abbreviations used throughout the metric levels are summarized in Table 3. Additional abbreviations are explained as necessary throughout.

Table 3. Summary of symbols and abbreviations used in the ecological metric calculations

Symbol	Description
$\boldsymbol{L}$	links
$\boldsymbol{i}$	product
$\boldsymbol{j}$	element
$\boldsymbol{L_i}$	number of links for product i
$\boldsymbol{L_j}$	number of links for element j
$\boldsymbol{S}$	number of "species" $(N_i + N_j)$
$\boldsymbol{N_i}$	number of products (material web) OR upper level/predator/plant (in ecology and network), weighted if available
$\boldsymbol{N_j}$	number of elements (material web) OR lower level/prey/pollinator (in ecology and network), weighted if available
$\boldsymbol{n}$	refers to either elements or products
$\boldsymbol{k_n}$	number of "species" n possible to connect to other "species" (both elements and products)
$\boldsymbol{E_n}$	number of actual links connecting "species" n
$\boldsymbol{p_i}$	proportion of interaction weight of "species" i out of the total

2.4.1. Network-level

At the network-level, product-element interactions are considered for most of the metric calculations.

Connectance

Ecology Definition	Proportion of realized ecological network interactions among the potential interactions (Blüthgen et al. 2008, Dunne, Williams, and Martinez 2002a). Note: this assumes that all interactions are possible
Ecology Example	Dunne et al. (2002b) studied connectance effect on robustness to biodiversity loss. They modeled species removal from food webs and measured secondary extinctions and compared this to the original connectance. Of the webs they studied, they found that low connectance webs displayed sensitivity from the beginning.
Industrial Ecology Example	Hardy and Graedel (2002) analyzed connectance for industrial parks to draw comparisons between the efficiency of material/nutrient use in an industrial park and food webs.
Network Example	Connectance, and other food web structure metrics, derive mainly from ecological network analysis. Other metrics are used to describe the structure of networks.
Equation/Calculation	For food web or network: $C = \frac{2L}{S(S-1)}$ (no cannibalism) OR $C = \frac{L}{S^2}$ (cannibalism) For bipartite network: $C = \frac{L}{(N_i * N_j)}$
Binary or Weighted	Binary (see weighted connectance for weighted version)
Maximum or Minimum Values	[0, 1]

Connectance is most often used in food web analysis to measure network complexity and structure (Dunne, Williams, and Martinez 2002a). In industrial ecology, it was applied to benchmark the complexity of industrial parks to that of food webs (Hardy and Graedel 2002, Wright et al. 2009, Layton, Bras, and Weissburg 2015). Dunne et al. (2002a) examined food webs and used connectance to determine what impact it could have on food webs and the potential for following the network "small-world, scale-free" degree distribution. They found that food webs are not small-world or scale-free, but that the network "topology is consistent with patterns found within those classes of networks." Connectance is applicable in critical material studies because it can be used to gauge the complexity of the system and its changes over time. Dramatic changes in connectance for material systems can raise flags for deeper study of what caused the change and if the impact manifests in other metrics.

Linkage Density

Ecology Definition	Number of links per species (Blüthgen et al. 2008) Weighted diversity of interactions per species (Morris et al. 2014)
Ecology Example	Typically used in conjunction with other food web metrics (e.g. connectance) to evaluate food web structure. Ledger et al. (2013) studied the effects of drought on food webs by examining changes in food web structure metrics, including linkage density. Linkage density and other food web structure metrics were also measured to understand how changes in the life stage of fish impacted the rest of the food web (Sánchez-Hernández, 2016).
Industrial Ecology Example	Linkage density was used in conjunction with other food web structure metrics, but these metrics were applied to an industrial park to compare its cycle of nutrients to that of a food web (Layton, Bras, and Weissburg 2015).
Network Example	Like connectance, linkage density is mainly used to describe food web structure and is not a common metric for network analysis.
Equation/Calculation	$LD = \frac{L}{N_i + N_j}$ (binary) $LD_q = \frac{1}{2}\left(\sum_{i=1}^{N_i} \frac{L_i}{L} 2^{H_i} + \sum_{j=1}^{N_j} \frac{L_j}{L} 2^{H_j}\right)$ (weighted) also calculated as the average of vulnerability and generality* *See generality, vulnerability, and Shannon diversity (H_i and H_j are Shannon diversity for products and elements respectively) (Bersier, Banašek-Richter, and Cattin 2002, Tylianakis, Tscharntke, and Lewis 2007, Dormann et al. 2009, Blüthgen et al. 2008)
Binary or Weighted	Binary/Weighted
Maximum or Minimum Values	[0, 1] (binary)

While connectance measures the proportion of realized links, linkage density (binary version) measures the number of links per species. This can also be viewed as the average number of species that any given species connects. The bipartite package for R that was used in this analysis utilizes the weighted version of linkage density and binary linkage density is referred to as “links per species.” In measuring the effects of drought on food webs, Ledger et al. (2013), found that both weighted and binary linkage density, as well as connectance, were unaffected by drought.

These results suggest that while a disturbance was occurring in the system, the species were able to maintain the same dietary variety. Linkage density translates to the material system in the same way. It can be measured whether or not the elements or products are maintaining the same number and diversity of relationships under disturbance. For this type of study, it is required that some type of disturbance analysis is conducted. Disturbance analysis is similar the ecological drought study, where changes, or perturbations, are made to the system to see how the network metrics respond when compared to the original values.

Links per Species (binary Linkage Density)

Ecology Definition	Mean links per species
Ecology Example	Links per species is the binary version of Linkage Density. For all examples, see linkage density.
Industrial Ecology Example	
Network Example	
Equation/Calculation	$LD = \frac{L}{S} = \frac{L}{N_i + N_j}$
Binary or Weighted	Binary
Maximum or Minimum Values	[0, S]

Weighted Connectance

Ecology Definition	Number of links out of those possible where each link is weighted
Ecology Example	Altena et al. (2016) studied connectance and weighted connectance relationships with stability and found weighted connectance to be positively correlated with stability whereas connectance had no relationship with stability. Stability in food webs mainly resulted from even weight distribution across the links.
Industrial Ecology Example	Like linkage density, it was included in the Layton et al. industrial park study (2015) to compare industrial complexity to food web complexity.
Network Example	Not a common metric in network analysis, mainly used to describe food web structure.
Equation/Calculation	$C_q = \frac{LD_q}{S}$ Weighted linkage density divided by the number of species, for derivation see Bersier et al. (2002)
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

Weighted connectance, like connectance, is a measure of complexity in food webs. It was included in the Ledger et al. (2013) study of drought effects on food web properties, and was found to be unaffected by drought. Altena et al. (2016) found a positive correlation between weighted connectance and stability, though the link strengths of the food webs analyzed were skewed toward weak interactions (majority of links had low weighting). For their study, stability was measured using interaction strength matrices, or Jacobian matrices, as described by May (1972). This type of analysis could be useful for critical material systems. If the factors contributing to stability of material systems can be understood and determined, the sustainability of a material web can be predicted.

Ecology Definition	Balance in number of species between the two levels (if positive, more upper-level species, and if negative, more lower-level species) (Dormann et al. 2009, Blüthgen, Menzel, Hovestadt, Fiala, and Bluthgen 2007)
Ecology Example	Blüthgen et al. (2007) examined the relationship between network asymmetry (web asymmetry) and specialization asymmetry. They found that when there were more plants than animals that the animals were more specialized, and in the case of more animals than plants, the plants were more specialized.
Industrial Ecology Example	N/A
Network Example	Symmetry is used in network analysis, but in a way that refers to the shape of the complex network. If the network is symmetrical, it is usually indicative of redundancy in the network, which potentially affects robustness (MacArthur, Sánchez-García, and Anderson 2008, Barabási 2012).
Equation/Calculation	$W = \frac{(N_j - N_i)}{S}$ and rescaled to fit max/min values
Binary or Weighted	Binary
Maximum or Minimum Values	[-1, 1] Note: calculation is rescaled

Web asymmetry determines whether there are more species in the upper-level or lower-level. A symmetrical web will have a value of zero, where the number of species in the upper-level is equal to that of the lower-level. In ecology, this was shown to be related to specialization (species are linked to fewer other species). Network analysis utilizes symmetry to indicate redundancy, which has potential to indicate robustness of the network. Robustness is when basic functions can still be performed after an internal or external perturbation or disturbance (Barabási 2012). Redundancy could translate to the material system, not via symmetry, but through the existence of substitutable elements. It would be considered redundant that two elements could perform the same function in a given product, but this is a good thing when it comes to the sustainability of the system.

Number of Compartments

Ecology Definition	Compartments are sub-webs that are not connected to other compartments (Jordan blocks in mathematics) (Dormann et al. 2009).
Ecology Example	Compartments may reveal evolutionary processes and likely change and evolve apart from the rest of the network (Guimarães et al. 2007). Compartments appear to result from several highly specialized species, which is how Tylianakis et al. (2007) explained the low compartmentalization of their host-parasitoid webs.
Industrial Ecology Example	N/A
Network Example	Compartments are not common for network analysis, clustering is more common (see Cluster Coefficient)
Equation/Calculation	N/A
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

In this study, the set-up of the material networks induces a single compartment. However, some ecologists have used strong links versus weak links to define compartments, but their method is more in-depth than the analysis here, see Krause et al. (2003) for derivation and examples of this compartment methodology. Tylianakis et al. (2007) found webs with several compartments and were able to determine partner diversity within each compartment (see compartment diversity below). Stouffer and Bascompte (2011) argue that increased compartmentalization can help buffer other parts of the food web from extinctions or disturbances. For critical materials, if compartmentalization in the material system could be increased, then it is possible that material shortages would have less impact on the rest of the system.

Ecology Definition	Diversity of each compartment (Shannon Diversity) (Dormann et al. 2009)
Ecology Example	Tylianakis et al. (2007) examined changes in food web metrics depending on host-parasitoid network habitat type and found no change in compartment diversity and linkage density across habitats.
Industrial Ecology Example	N/A
Network Example	Compartments are not common for network analysis, clustering is more common (see Cluster Coefficient)
Equation/Calculation	$CD = \exp\left(-\sum_{i=1}^{S} p_i(\ln p_i)\right)$ where, p_i is the fraction of each element-product pair in the compartment (Partner diversity calculated for each compartment, which is Shannon diversity to the power of e, this converts the result into "effective number of partners" or number of species (Dormann et al. 2009))
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, ln(S)]

Ecology Definition	Average of connectance per species or the number of realized links per possible links for each species averaged over the entire network (in group-level it is calculated for the upper- and lower-levels) Note: this assumes all links are possible and that links flow in both directions (Dormann et al. 2009)
Ecology Example	Dunne et al. (2002a) used clustering coefficients to determine if food webs followed the same structure as small-world networks and found that food webs did not fit small-world criteria because of low clustering.
Industrial Ecology Example	DeLaurentis and Ayyalasomayajula (2009) explored network analysis as a tool for understanding complexity in industrial ecology, specifically focusing on air transportation. They note that higher clustering coefficients are indicative of robustness, similar to compartments, and to some extent, efficiency. Their rationale resulted from simulations illustrating for air transportation that higher clustering meant more direct routes and less fuel required per passenger.
Network Example	Introduced as a defining criteria for small-world networks by Watts and Strogatz (1998). Newman (2001) analyzed random versions of scientific collaboration networks (authors and papers) and found clustering coefficients to follow a power law where a large number of nodes yield a lower clustering coefficient.
Equation/Calculation	$C_n = \frac{2E_n}{k_n(k_n-1)}$ then averaged: $\bar{C} = \frac{1}{S}\sum_{n=1}^{S} C_n$
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

It is interesting that high clustering coefficients were deemed valuable in the industrial ecology example for efficiency and robustness, whereas food webs seemed to have low clustering and are commonly hailed for their efficiency and robustness (Hardy and Graedel 2002). This may be due to a much larger/smaller number of nodes in the food webs compared to the air transportation model, although it was not clear how many nodes the air transportation network contained (DeLaurentis and Ayyalasomayajula 2009, Newman 2001, Dunne, Williams, and Martinez 2002a). Similar to compartmentalization, clustering coefficient could be an indicator of robustness in critical material systems because of the weaker connections between clusters preventing perturbations from spreading. Nevertheless, this is a network property, so the system as a whole may be able to carry on its functions, but if an element is unavailable, its cluster will probably have difficulty functioning. In a sense, highly clustered systems are likely robust to random events, but not targeted events (Barabási and Frangos 2014).

Nestedness

Ecology Definition	A perfectly nested food web is "when rows and columns are ordered by decreasing number of links, links of each row and column exactly represent a subset of the previous ones" (Blüthgen et al. 2008). Nestedness "temperature," T, is a measure of the departure from a perfectly nested web, so when $T = 0°$, the web is perfectly nested. For $N = 0$, nestedness is high, and for $N = 100$, the web is chaotic (Dormann et al. 2009).
Ecology Example	Bascompte et al. (2003) developed the method for application of nestedness to bipartite networks and found mutualistic webs (both groups benefit, i.e. plant-pollinator) were not random or compartmentalized, but highly nested.
Industrial Ecology Example	Bustos et al. (2012) show that the presence and absence of industries in international and domestic economies form networks that are highly nested and consistent over time. The former is likely a result of industries being complementary.
Network Example	Nestedness is an ecological network concept, typically not used in traditional network analyses.
Equation/Calculation	$N = \frac{(100° - T)}{100°}$ The full derivation of T is available in the supplementary information of Bustos et al. (2012) and nestedness is commonly calculated using software (Tylianakis et al. 2010)
Binary or Weighted	Binary
Maximum or Minimum Values	[0, 100]

Weighted Nestedness

Ecology Definition	Weighted nestedness is the same as binary nestedness, but weighted by interaction frequency (Dormann et al. 2009). When $N_q = 1$, the web has maximum nestedness, and at 0, complete chaos.
Ecology Example	Galeano et al. (2009) recently developed this version of nestedness; therefore, few studies have incorporated it into analysis.
Industrial Ecology Example	
Network Example	
Equation/Calculation	Calculation for weighted nestedness is computationally extensive, for derivation see Galeano et al. (2009)
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, 1]

Ecology Definition	Another weighted measure for nestedness. Dormann et al. (2009) point out that analysis by Almeida-Neto et al. (2011, 2008) highlights that this is a better and more consistent measure of nestedness. "High values indicated nestedness" (Dormann et al. 2009).
Ecology Example	Almeida-Neto et al. (2008) developed the weighted NODF to incorporate the actual abundance gradient of species and account for species contribution.
Industrial Ecology Example	Bustos et al. (2012) also used weighted NODF in their industrial ecosystem analysis (see Nestedness for additional information).
Network Example	See Nestedness
Equation/Calculation	For equation and derivation, see exhaustive explanation in Bustos et al. (2012) supplementary information and a review of nestedness measures by Almeida-Neto et al. (2008).
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

Tyliankis et al. (2010) describe nestedness as "analogous to the peeling of layers from an onion." In a nested network, as specialists are lost, the center composed of generalists exists intact. Various methods exist and have been both criticized and extended, and methods that are accepted are computationally intensive for larger webs (Dormann et al. 2009). Some studies exist for nestedness, but mostly in ecological network analysis. Few are available from industrial ecology, and nestedness is not a network analysis metric by origin. Although nestedness has shortcomings, Tyliankis et al. (2010) point out the reasons it is a useful characteristic for conservation of species. In mutualistic networks, nestedness can buffer against secondary extinctions and temporal fluctuations in pollinators that are specialists. This means that when a species goes extinct, it is less likely that more extinctions will occur as a result. In the material web, with higher nestedness, if an element is restricted or scarce in some way, other products/elements in the system are unlikely to be lost. Additionally, if the lower level (elements) experience variation in existence and quantity, and the system is nested, then the system overall is buffered against those changes in element availability.

Ecology Definition	Measures the imbalance between the interaction strength of a species pair (interaction between upper level node and lower level node). Positive values are indicative of higher dependence on the upper level (Dormann et al. 2009).
Ecology Example	Bascompte et al. (2006) highlight various features of mutualistic and antagonist networks that result from asymmetry. They point out that asymmetry is usually high for competitive interactions and appears to be crucial for biodiversity and coexistence in mutualistic networks. An example of a highly asymmetric interaction: "if a plant depends strongly on an animal species, the animal depends weakly on the plant" (Bascompte, Jordano, and Olesen 2006).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	$AS_{ij} = \frac{(b_{ij} - b_{ji})}{(b_{ij} + b_{ji})}$ where $b_{ij} = \frac{a_{ij}}{A_i}$ and $b_{ji} = \frac{a_{ij}}{A_j}$ where a_{ij} is proportion of interactions for i (i species with partner species j), which translates to the interaction strength between i and j
Binary or Weighted	Weighted
Maximum or Minimum Values	[-1, 1]

Positive values indicate that the network has a higher dependence on the products (upper trophic level). At the species level, an important thing to note about this metric is singleton or rare species will receive high values resulting in high dependence, but, in the R bipartite package, singleton species are omitted prior to calculation (Dormann et al. 2009). Bascompte et al. (2006) refer to this metric as 'dependence' asymmetry and calculate absolute values. Based on their example of highly asymmetric interaction strength, in the material system, a highly asymmetric interaction is if the product depends strongly on an element, the element has a weak need for the product. This means that for highly asymmetric material networks, there are likely a larger number of important elements to the products considered.

Specialization Asymmetry

Ecology Definition	Asymmetry of specialization based on d' (see d'), which is not sensitive to web dimensions (number of upper level species versus number of lower level species) (Dormann et al. 2009). Higher values indicate the upper level is more specialized.
Ecology Example	See Ecology Example in "Web Asymmetry"
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	$SA = \frac{(\langle d'_j \rangle - \langle d'_i \rangle)}{(\langle d'_i \rangle + \langle d'_j \rangle)}$ where $\langle d'_j \rangle$ is the average specialization (d') of lower level and $\langle d'_i \rangle$ is the average specialization of the upper level (see d')
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

Positive values indicate higher specialization of the product-level, which would indicate that overall the products require fewer elements. If specialization asymmetry is shown to decrease over time, then it will highlight that the products are relying on an increasing number of elements which could be troublesome for those products if the elements experience supply disruption. For example, if products rely on a specific group of elements, and production for those elements is concentrated in a single country that suddenly decreases exports, those products are vulnerable to price spikes.

Ecology Definition	Alternative to interaction diversity. Fisher's alpha is only possible for "genuine counts of individuals" (Oksanen et al. 2016).
Ecology Example	Karlson et al. (2004) used Fisher's alpha and species estimations to determine if undersampling was an issue in their ecological community study of coral reef biodiversity gradient. Fisher's alpha is "widely recognized as a stable, relatively sample-size-independent diversity measure at both local and regional scale, and…often used to compensate for undersampling" (Karlson, Cornell, and Hughes 2004). They determined that undersampling was not an issue for their community. Sampling is a common issue when it comes to food webs and ecological networks because it is dependent on physical measurements or sightings (Krebs 2014, Magurran 1988).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	α and x are the main coefficients, determined using S (number of species) and N (number of each individual species): $S = -\alpha \log_e(1-x)$ $N = \frac{\alpha x}{(1-x)}$ a full derivation is available via Fisher et al. (1943), where α is considered "the index of diversity" of a population
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

Fisher's alpha, an alternative to other diversity measures, can only be calculated for data that represents actual species counts or measured in real numbers. This makes calculations for a material web with an interaction strength measured in mass impossible. Despite the fact that it is not applicable to the material web measured in mass, it does have benefits as a diversity index as pointed out by Karlson et al. (2004).

Shannon Diversity

Ecology Definition	Shannon diversity is a measurement of species diversity based on interactions (i.e. network matrix entries) (Dormann et al. 2009).
Ecology Example	Diversity of soil bacteria was studied and linked to differences in soil pH by Fierer and Jackson (2006).
Industrial Ecology Example	Wright et al. (2009) studied diversity of eco-industrial parks for comparison to ecological systems, and Ryen et al. (2014) studied the change in household product functional diversity over time.
Network Example	Rafols and Meyer (2010) used diversity as an indicator of interdisciplinary studies using bionanoscience articles as a case study. They found that the disciplinary diversity for most articles was relatively the same and there were several "fuzzy and overlapping bodies of knowledge" indicating that interdisciplinary was possibly a misnomer (Rafols and Meyer 2010).
Equation/Calculation	$H' = -\sum_{i=1}^{S} p_i (\ln p_i)$
Binary or Weighted	Weighted
Maximum or Minimum Values	$[0, \ln(S)]$

Shannon diversity is actually a measure of entropy and reflects the uncertainty in predicting the next species to be sampled from the community (Jost 2006). This measure, traditionally referred to as "Shannon-Wiener" diversity, is based on information theory and quantifies the amount of order or disorder in a system. Typically, it measures code content, as bits, but the units change based on the log base used. Log_2 is the original base from information theory and ensures the result is in "bits" (Pielou 1975). Magurran (2013) points out that most ecologists have dropped this as it is not relevant and use natural log (ln) or log base 10 instead. They also argue that Shannon diversity is not the best metric for diversity because of its sensitivity to sample size, but it is widely used because it has been used as a baseline for many long-term biodiversity studies (Magurran 2013). Shannon's is most appropriate for sample sizes that are indefinitely large, but has been shown to also be a good diversity measure with small sample sizes (Pielou 1975, McDonald and Dimmick 2003, Dimmick and McDonald 2002). Shannon diversity is a good measure to use for criticality studies of material systems, much like connectance, it is widely used amongst many disciplines, so it is useful for benchmarking the material web with other systems. Higher values indicate higher diversity, and in this metric, both the variety of "species" and relatively equal abundances contribute to higher values. Despite the difficulties in choosing an appropriate metric for diversity quantification, see diversity metric comparison by McDonald and Dimmick (2003), the more important implication is what the value of the diversity measurement means for the system.

A major implication of diversity that has been widely debated is that higher diversity is indicative of system stability. While definitions of stability vary, the reigning definition for ecological studies is accounts for equilibrium stability and equilibrium resilience. Equilibrium stability is when the system returns to equilibrium after small perturbation, and given no perturbations, has no change in population densities over time. Equilibrium resilience says that stability increases with decreasing time to return to equilibrium after a perturbation (McCann 2000). Given this, ecosystem stability is typically based on notions that after perturbations, the system returns to equilibrium quickly and population density is largely unaffected.

The diversity-stability relationship has been of significant interest to ecologists, specifically with respect to species conservation, and more recently because of Earth's alarming biodiversity loss (McCann 2000). McCann (2000) conducted an extensive review of the diversity-stability debate and concluded that, on average, diversity results in stability of ecosystems. However, they note that diversity is not guiding the relationship, rather it is the result of the system's ability to maintain species and functional groups and response to change. Therefore, diversity can indicate whether a system is likely to be stable, but not what factors are driving the stability. This is where other ecological network metrics become important. Compartments and nestedness ensure redundancy so perturbations do not spread throughout the system. Generalists are likely a common feature to diverse systems, and these species types have adaptable diets, which is beneficial in the event of extinctions.

For a criticality application of the diversity-stability relationship, it is important to determine what definition of stability is needed. In the ecological application of stability, the system is expected to return to equilibrium, whereas general stability can return to a non-equilibrium state after perturbations. For critical material systems, it seems that the important version of stability is one that will ensure long-term sustainability of the system. Because of technological advances and continuous changes, a material system should be expected to change and evolve and never truly exist in an equilibrium state when considering the long-term, so a general stability and resilience definition is appropriate. This means that the material system will return to its previous state after a perturbation within a reasonable amount of time. Material systems should then be considered stable if visibly undergoing perturbations or changes in diversity and still returning to the previous state within a relatively short amount of time. If the system is not experiencing changes in diversity, it could mean that it is not being perturbed or is highly resilient to perturbations. In terms of material criticality, a perturbation is likely some type of supply disruption, change in technology or product demand, or even an economic disturbance.

While diversity-stability is a reigning implication for diversity measurements, it is important to note that diversity studies vary greatly in their application and implications, which is reflected in the variety of examples presented in the Shannon diversity table.

	Interaction Evenness
Ecology Definition	Evenness measures similarity of the abundances of each species, or the balance of species across the system. High evenness indicates that most species have the same abundance and that no single species is dominating the system (Magurran 2013).
Ecology Example	In their study of habitat modification on host-parasitoid food webs, Tylianakis et al. (2007) found that evenness declined with habitat modification. Blüthgen et al. (2008) note that this represents heterogeneity between the two trophic levels, but does not represent changes in specialization.
Industrial Ecology Example	Applied to consumer electronics by Ryen et al. (2014) and found that the system was initially uneven as CRT TVs and desktop computers dominated, but over time became more even as people began using multiple mobile devices.
Network Example	N/A
Equation/Calculation	This specific version is based on Shannon Diversity (H'): $E_s = \frac{H'}{H'_{max}} = \frac{-\sum_i \sum_j p_{ij} \ln{(p_{ij})}}{\ln{(L)}}$ The difference here is that each interaction (element-product or predator-prey pair) is considered as its own "species" and the total number of "species" is equal to the number of links. This may not seem correct, but it is useful to determine if a single interaction pair is dominating the network.
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

Evenness is a measure of the equality amongst species abundance where higher equality indicates higher evenness. Evenness is one component of diversity along with species richness. Species richness captures the variety of species, while evenness captures the balance amongst those species. Evenness is commonly calculated by dividing a diversity metric by its maximum value, as shown by "Interaction Evenness" (Krebs 2014). However, there have been several other proposed evenness measures, including the Alatalo interaction evenness, an evenness measure that is useful for networks (Dormann et al. 2009, Muller et al. 1999, Alatalo 1981, Krebs 2014). For critical material systems, identifying if the system contains a disproportionate amount of one or a few element-product pairs can mean two things. First, those element-product pairs that are abundant are particularly vulnerable to both a supply disruption of the element and an increase in demand for the product. Second, the system may be relying on that specific pair of element and product (indicative by low evenness), but especially if evenness declines over time. If the system is slowly becoming less even and a single element-product pair is dominating, the system is vulnerable to disruptions involving that pairing.

Alatalo Interaction Evenness

Ecology Definition	Alternative evenness measure that was developed by Alatalo (1981) and proposed by Muller et al. (1999) as it "is particularly robust to the presence of outliers."
Ecology Example	This particular evenness metric was used by Muller et al. (1999) to confirm similarity between species compositions of four categories of species.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	$N_1 = \exp\left(-\sum_i \sum_j p_{ij}\, ln\left(p_{ij}\right)\right)$ $N_2 = \left(\sum_i \sum_j {p_{ij}}^2\right)^{-1}$ Alatalo Evenness is then $F_{2.1} = \frac{N_{2-1}}{N_1 - 1}$ See Alatalo (1981) for full derivation of this index.
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

	H_2'
Ecology Definition	Measures specialization at the network-level and ranges from 0 (no specialization) to 1 (complete specialization) (Dormann et al. 2009).
Ecology Example	This measure was developed to overcome limitations of binary specialization metrics (i.e. connectance) and was found to be unaffected by network size or sampling intensity (Blüthgen, Menzel, and Blüthgen 2006). It is based on Shannon diversity and reflects the specialization of the entire network for comparing between networks.
Industrial Ecology Example	N/A
Network Example	This is a relatively new metric and developed for the purpose of analyzing biological networks.
Equation/Calculation	For a resource-consumer network: $H_2 = -\sum_{i=1}^{r}\sum_{j=1}^{c}(p_{ij}\ln(p_{ij}))$ which is the two-dimensional version of Shannon diversity, to find the specialization, the max and min are compared: $H_2' = \frac{H_{2max}-H_2}{H_{2max}-H_{2min}}$ (see Blüthgen et al. (2006) for full derivation)
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, 1]

H_2' is a measure of specialization of the entire network based on the maximum specialization expected (Dormann et al. 2009). It was developed to improve ecologist's understanding of specialization patterns across networks (Blüthgen, Menzel, and Blüthgen 2006). For materials, specialization can indicate that an element is important for a function of a product, but at the network level it would indicate that several elements are important for the products (or the only elements within the system that the product is using). Like ecological network analysis, this is useful to compare the specialization across material systems. Highly specialized networks may be of concern because the system has a lot of important elements or specialized products.

2.4.2. Group-level

At the group-level, products and elements are considered as "groups." The products represent the higher-level (HL) and the elements represent the lower-level (LL). In the discussions, HL and LL are sometimes referred to as upper-level and lower-level, respectively.

Number of Species

Ecology Definition	Number of species in each trophic level and typically used to illustrate the size of the bipartite network (Dormann et al. 2009).
Ecology Example	N/A
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	N_i or N_j
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

Number of species is simply the number of each "species" within each level. Mainly used for comparing across networks, especially if bipartite size is suspected to affect metric results.

Mean Number of Links

Ecology Definition	Number of links per species averaged across each group
Ecology Example	
Industrial Ecology Example	Similar to links per species at the network level, or the binary version of linkage density. See linkage density for relevant examples.
Network Example	
Equation/Calculation	$\bar{L}_x = \frac{\sum_{i=1}^{x} L_x}{N_x}$ where x is either product, i, or element, j for all products and elements
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

Mean number of links is a group level and binary version of linkage density. At this level, this measurement is not as prevalent in studies.

Mean Number of Shared Partners

Ecology Definition	Number of species in the other level that any two species interact with, for example, for the lower level, it will produce an average number of upper level species that are shared by any two lower level species (Dormann et al. 2009).
Ecology Example	This measurement is based on the work of Roberts and Stone (1990, 1992) where they determined the number of islands shared by a pair of species.
Industrial Ecology Example	N/A
Network Example	In a network analysis of scientific journal authorship, this would be number of journal articles shared in authorship by a pair of scientists or number of authors a pair of journal articles share, on average.
Equation/Calculation	See work by Roberts and Stone for derivation and matrix operations (1992, 1990)
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

Mean number of shared partners is based on the distance matrix between species (Dormann et al. 2009). Although not widely discussed in ecological network analysis, this metric points out how similar two species are likely to be at either level. For example, at the individual level, in a material system, this would indicate how many products that two elements share. Therefore, it represents similarity between the two and a likelihood of co-occurrence.

Weighted Cluster Coefficient

Ecology Definition	Weighted average connectance per-species. See cluster coefficient in the network level for binary version.
Ecology Example	See cluster coefficient in network level metrics.
Industrial Ecology Example	
Network Example	
Equation/Calculation	Calculation, derivation, and additional discussion can be found via documentation of the tnet package and via work by Opsahl et al. (Opsahl 2007, Opsahl and Panzarasa 2009, Opsahl 2013).
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

The weighted cluster coefficient is computationally challenging, as discussed by Opsahl et al. (2009), and ignores some feature of the network such as direction of interactions. Because this metric is for the group-level, it indicates how clustered the elements or products are within each group. As mentioned previously, clustering can be an indicator of robustness, so long as random attacks are experienced and not necessarily targeted attacks. High clustering also protects the rest of the system from being affected from perturbations in other parks of the network. Therefore, this is indicative of the robustness of the group (element or product) to supply disruptions or other effects.

Niche Overlap

Ecology Definition	Mean similarity in interaction patterns amongst a species group, values close to 0 indicate no common patterns and values near 1 indicate perfectly overlapping interaction patterns (Dormann et al. 2009).
Ecology Example	Originally suggested in ecology as a measure of competition, but it is debated whether or not the relationship between overlap and competition exists, so it is mostly used as a community descriptor (Krebs 2014).
Industrial Ecology Example	Not formally explored, but in the case of the household electronics, as the household product network evolved multi-functionality of individual products increased, which likely reduced niche overlap (Ryen et al. 2014). In this instance, the household is vulnerable if the multi-functional product is lost or damaged. For example, a consumer relies on their mobile phone as a camera, computer/email, telephone, and more. If this phone is damaged, and the consumer does not have a separate camera, then the camera functionality is lost to their network of products and they have no back up for taking photographs.
Network Example	Ecology's use of niche overlap as a competition measurement likely stems from the concept of niches in business. Podolny et al. (1996) examine the network of the worldwide semi-conductor industry and hypothesize that crowding (niche overlap) decreases growth rates, but find that status also plays a role in growth rates. They argue that niche overlap usually corresponds to similar technological patterns.
Equation/Calculation	There are several ways to calculate niche overlap, but the R bipartite package utilizes "Horn-Morisita similarity," which is described along with others via Krebs (2014). Krebs (2014) also points out that it does not necessarily matter which version is used, results are usually the same.
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, 1]

Niche overlap is a measure of the similarity of interactions between species in a trophic level. It has been used in ecology to quantify competition, and this is likely a translation from its use in business. Still, ecologists are unsure if it is a measure of competition or similarity. At the very least it represents similarity of interactions, which could signify that the species are performing similar functions. Having similar functions amongst a group is likely for a material web, particularly within the elements, and if so, could be a measure of redundancy. In terms of criticality, a niche overlap could be a potential measure for likelihood of substitution. In criticality, substitution is a common term for using non-critical elements in place of critical elements in to guard against issues resulting from supply disruption (i.e. price spikes). We know from ecological studies that this type of redundancy is good for the network because in the event of an extinction (or supply disruption), the network has back-up species performing that function.

	Togetherness
Ecology Definition	Mean number of co-occupancies across all interactions, measures the distributional pattern between two species (Dormann et al. 2009). Values cannot be compared across each group due to different numbers of species.
Ecology Example	Roberts and Stone (1990, 1992) found the species existing on the same islands increased the togetherness score of the systems they studied. Typically used for biogeographical studies, but can be applied to plant/host and pollinator networks.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	The matrix is scanned for sub-matrices for perfect matches of co-occurrences and co-absences: $\begin{pmatrix} 0 & 1 \\ 0 & 1 \end{pmatrix}$ these are counted for each pair-wise interaction then averaged over each group, based on the work of Stone and Roberts (1992) (Dormann et al. 2009).
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

While niche overlap measures the likelihood of two species interacting with another species, togetherness is the likelihood of upper-lower pairs, or interactions, occurring or not occurring at the same time. Higher togetherness values are indicative of one species occurring because another species is occurring. For the elements, if togetherness is high, the existence of a specific element-product pair means another specific element-product existence is likely. Alternatively, high togetherness means that it is common for certain pairs to occur together and interact with the same species. It was originally proposed for biogeographical studies in ecology, meaning species-location networks, but is suitable for host/plant-pollinator networks as it measures the similarity in distributional pattern between two species (Dormann et al. 2009, Stone and Roberts 1992). For togetherness, the translation to the material system, in terms of applicability or implications, is challenging to discern. At best it can be used to say that species (elements or products) in a given group (with high togetherness) are likely to occur together and likely to be interacting with the same product or element from the other group.

C-Score

Ecology Definition	C-Score is the normalized mean number of checkerboard combinations across all species in each group. Values close to 1 indicate repelling forces, or competition, values close to 0 indicate no repelling forces or disaggregation. Scores cannot be compared across each group due to different numbers of species. (Dormann et al. 2009)
Ecology Example	C-Score is a biogeographic metric, much like togetherness and was also presented by Stone and Roberts (1992), but mostly represents non-co-occurrence or likelihood of species to not occur together (Dormann et al. 2009).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	See derivation and explanation by Stone and Roberts (1992)
Binary or Weighted	Binary
Maximum or Minimum Values	[0, 1]

	V-Ratio
Ecology Definition	V-Ratio is a group-level ratio of variance in species numbers to variance of interaction numbers (Dormann et al. 2009). V-ratios larger than 1 indicate positive associations, while values less than 1 indicate negative associations, and large or small values can indicate competition (Schluter 1984).
Ecology Example	Schluter (1984) presents this metric as a way to evaluate species interactions as positive or negative and speculates what interaction type could cause such interactions (competition, predation, mutualism, or none) and gives examples of each of these interaction types. They point out that without an understanding of the biological system, the result is only a statistic and not meant for interpretation.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	See derivation and explanation in Schluter (1984)
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

C-score and V-ratio, like togetherness, are biogeographical metrics from ecology that seek to understand how various species exist and interact with one another and are based solely on presence/absence data (binary) (Schluter 1984). The applications for this do not appear to translate very well to the material system because the ecological interactions, like competition, are related to behavior which materials do not have. Co-occurrence metrics like togetherness are probably better than that of the competition measurements (c-score and v-ratio), though competition measurements could be helpful for understanding instances where products may be competing for elements, but at the aggregate group-level this does not seem very helpful.

Discrepancy

Ecology Definition	The number of mismatches between a binary matrix and a perfectly nested matrix (Dormann et al. 2009). Smaller values reflect higher nestedness (Ulrich and J Gotelli 2007).
Ecology Example *Industrial Ecology Example* *Network Example*	Ulrich and Gotelli (2007) found Discrepancy to be less susceptible to error than the traditional nestedness temperature calculation, which falsely identifies nested networks. For nestedness examples, see Nestedness.
Equation/Calculation	"The matrix is sorted by marginal totals, yielding a matrix A. Then, all 1s in A are 'pushed' to the left to maximally compact the matrix, yielding P. Discrepancy is now simply the number of disagreements between A and P, divided by two (to correct for the fact that every 'wrong' 1 will necessarily generate a 'wrong' 0)" (Dormann, Gruber, and Fruend 2008).
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

Discrepancy is an alternative measurement for nestedness that focuses on the group level and overcomes limitations of the temperature nestedness measurement (Ulrich and J Gotelli 2007). For examples and discussion about criticality implications, see Nestedness in network level.

Extinction Slope

Ecology Definition	Slope of the extinction sequence for a level following random exterminations of species in the other level. Extinction slope for the upper level is robustness of the upper level to extinctions in the lower level and vice versa. The higher the slope, the less the network is affected by extinctions (Dormann et al. 2009).
Ecology Example	Memmott et al. (2004) studied the effects of extinction on two plant-pollinator networks, they noted that plant diversity fell quickly with removal of the highest linked pollinators, but actual declines were essentially linear when compared to other removal patterns.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	Based on a power law function $y = 1 - x^a$ where a is the "slope"
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

Extinction slope measures the robustness of a species group to extinctions in the other group. This is an important metric when it comes to material criticality because it indicates how well the product group will fare given a supply disruption of the elements. The same can be said of robustness.

Robustness

Ecology Definition	Robustness is the area under the extinction slope curve, the higher level value indicates the robustness to extinction of the higher level to extinctions in the lower level, much the same as extinction slope (Dormann et al. 2009).
Ecology Example	See example for extinction slope. Burgos et al. (2007) determined that highly nested mutualistic networks were the most robust to extinctions.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	Burgos et al. (2007) improved upon the work of Memmott et al. (2004) and developed a single parameter, R, for robustness. R = 1 indicates the curve decreases slowly until almost all species are eliminated R = 0 indicates the curve decreases abruptly as soon as any species is lost
Binary or Weighted	Binary
Maximum or Minimum Values	[0, 1]

Functional Complementarity

Ecology Definition	Measure of niche complementarity or the function of sharing interactions and should be highly correlated with niche overlap, but is binary (Dormann et al. 2009).
Ecology Example	See niche overlap
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	"computed as the total branch length of a 'functional dendrogram' based on qualitative differences of interactions of one level with the other" (Dormann et al. 2009)
Binary or Weighted	Binary
Maximum or Minimum Values	N/A

Functional complementarity is similar to niche overlap, but a binary calculation. See niche overlap table and discussion for criticality implications of species sharing interactions.

Partner Diversity

Ecology Definition	Weighted mean of the Shannon diversity for each level (Dormann et al. 2009). However, Shannon diversity is calculated using log base e (Dormann 2011).
Ecology Example	Dormann (2011) analyzed various metrics for quantifying specialization in pollination networks and found that partner diversity was a redundant measurement, as it was quantifying similar properties as degree and betweenness. They also point out that low values of partner diversity are indicative of specialization.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	$PD = -\sum_{i=1}^{S} p_i(\ln p_i)$
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, S]

Partner diversity measures the diversity of interactions amongst species groups, but is also determined for the species level. Low values of partner diversity typically indicate that the species is specialized, or interacting with few other species. This quality is of interest to critical material systems, but more-so at the species level where specialization of an element to a product or vice-versa perhaps signifies its importance or the importance of the relationship. Increasing values of partner diversity, especially at the individual species level, indicate elemental importance to an increasing number of products, mimicking the factor of "importance to technology" facet of the criticality matrix.

Generality

Ecology Definition	Mean number of prey species per predator or number of lower level per upper level, can be weighted or binary (Dormann et al. 2009).
Ecology Example	The newness of weighted generality means that few studies have utilized it. Tylianakis et al. (2007) found generality and vulnerability to change with habitat modification.
Industrial Ecology Example	Analyzed in conjunction with other food web structure metrics for industrial parks to compare its cycle of nutrients to that of a food web (Layton, Bras, and Weissburg 2015). Generality and vulnerability were used to understand if more/less consuming entities existed in the industrial park. The differences, they discovered, highlight that the structure of eco-industrial parks is different than the structure of food webs.
Network Example	N/A
Equation/Calculation	$G = \frac{N_j}{N_i}$ (binary) for weighted calculation, see weighted Linkage density, and see derivation from Shannon's diversity in Bersier et al. (2002)
Binary or Weighted	Binary/Weighted
Maximum or Minimum Values	N/A

Vulnerability

Ecology Definition	Mean number of predator species per prey or number of upper level species per lower level, can be weighted or binary (Dormann et al. 2009).
Ecology Example	See Generality.
Industrial Ecology Example	
Network Example	
Equation/Calculation	$V = \frac{N_i}{N_j}$ (binary) for weighted calculation, see weighted Linkage density, and derivation from Shannon's diversity in Bersier et al. (2002)
Binary or Weighted	Binary/Weighted
Maximum or Minimum Values	N/A

Generality and Vulnerability are important for understanding the balance between the two levels. For criticality, vulnerability is especially useful. If the number of products per element (vulnerability) increases, then the elements overall are becoming more important to the products and a supply disruption will affect more products.

2.4.3. Species-level

At the species-level, metrics were calculated for each individual product and individual element present in the system for that year and country.

Degree

Ecology Definition	Number of links per species
Ecology Example	Degree is one of the simplest measures for determining whether or not species are "generalists" or "specialists" (Dormann 2011). High degree is indicative of generalist behavior. A pollinator that visits several species of plants would be considered a generalist.
Industrial Ecology Example	N/A
Network Example	In networks, degree "measures the involvement of the node in the network" (Opsahl, Agneessens, and Skvoretz 2010).
Equation/Calculation	$L_i \; or \; L_j$
Binary or Weighted	Binary
Maximum or Minimum Values	$[1,\ N_n]$

Normalized Degree

Ecology Definition	Number of links per species out of the total possible links (scales degree from 0-1) (Dormann 2011, Dormann et al. 2009)
Ecology Example	Normalized degree measures the same thing as degree, but it is normalized based on the number of species. See Degree for examples.
Industrial Ecology Example	
Network Example	
Equation/Calculation	$D_N = \frac{L_n}{N_n}$
Binary or Weighted	Binary
Maximum or Minimum Values	$[0, 1]$

Degree is used in networks to understand how involved a node is within the network, but in ecology, it is used to describe specialization. Network analyses, and even ecologically analyses, are usually much more interested in the distribution of degree (Dunne, Williams, and Martinez 2002a, b, Dormann 2011). Degree distribution dictates the underlying structure and evolution pattern of the network (Albert and Barabási 2002). Refer to the discussion on Connectance in the network-level metrics for additional information about degree distribution and ecological networks. For criticality, degree can reflect both the network and ecological application. For example, at a basic level it is indicative of how involved the element or product is within the system, but as discussed, specialization is also of interest for materials. Specialization of products means that the product is using very few of the elements, which could indicate that the element is important to the product. Obviously, this conclusion is dependent on the functional relationship between the element and the product. On the other hand, a generalist element will affect several products if a supply disruption or shortage occurs.

Betweenness

Ecology Definition	Measure of species centrality focusing on proximity to other nodes (Dormann et al. 2009)
Ecology Example	Proposed as a measure of generalization in pollination networks by González et al. (2010). See discussion for additional information.
Industrial Ecology Example	N/A
Network Example	Network analysis points out that betweenness metrics "assess the degree to which a node lies on the shortest path between two other nodes, and are able to funnel the flow in the network" (Opsahl, Agneessens, and Skvoretz 2010). Basically, betweenness represents how much influence a node has over other nodes or how much power or control they may have to change the flow of information.
Equation/Calculation	$BC_k = 2\sum_{i<j;k\neq i}\frac{g_{ij}(k)/g_{ij}}{(n-1)(n-2)}$, where: n is the number of nodes g_{ij} is the number of shortest paths between the nodes $g_{ij}(k)$ is the number of shortest paths between i and j that go through k k is each species
Binary or Weighted	Binary
Maximum or Minimum Values	[0, 1]

González et al. (2010) found that betweenness and closeness were indicative of generalists. Generalists, they argue, are typically keystone species to the network for two reasons: 1) interacting closely with other species, and 2) connecting typically unconnected subnetworks. The close interaction is a result of high closeness, and connecting subnetworks is a factor of high betweenness. Centrality measures altogether are useful for criticality applications. Betweenness and closeness in particular have been used in ecology to identify generalists, specialists, and keystone species, which are promising concepts for criticality. Application of these metrics will require careful consideration of what it means to be a "specialist," "generalist," or "keystone species" with respect to individual elements or products. What does not translate so well with centrality measures is the network applications related to "flows" of information, transportation pathways, etc. It should also be noted that for bipartite networks, the weighted versions of betweenness and closeness have computational challenges as discussed by Opsahl regarding the projection of the two-mode bipartite to a one-mode before centrality calculations (Opsahl 2013, Opsahl, Agneessens, and Skvoretz 2010).

	Weighted Betweenness
Ecology Definition	Betweenness that accounts for network weighting, note that it often differs from its binary version (Dormann et al. 2009)
Ecology Example	
Industrial Ecology Example	Weighted betweenness is the weighted version of betweenness. See Betweenness examples and discussion.
Network Example	
Equation/Calculation	See derivation and discussion by Opsahl et al. (2010)
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

Closeness

Ecology Definition	Closeness is a centrality measure describing the average path length to other nodes (normalized by species) (Dormann et al. 2009).
Ecology Example	A low closeness value is indicative of species specialization
Industrial Ecology Example	N/A
Network Example	Closeness means that a node is "in a position to reach others quickly to access resources, such as information or knowledge" (Opsahl, Agneessens, and Skvoretz 2010).
Equation/Calculation	$CC_k = \sum_{j=1;j\neq k}^{n} \frac{d_{jk}}{n-1}$ d_{jk} is the average distance between nodes
Binary or Weighted	Binary
Maximum or Minimum Values	$[0, 1]$

Weighted Closeness

Ecology Definition	Closeness that accounts for network weighting, and usually yields similar results to its binary counterpart (Dormann et al. 2009).
Ecology Example	
Industrial Ecology Example	Like weighted betweenness, this is the weighted version of closeness. See Closeness examples and discussion.
Network Example	
Equation/Calculation	See derivation and discussion by Opsahl et al. (2010)
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

Species Strength

Ecology Definition	Sum of interactions for a species, but based on proportional interactions, otherwise it equals the abundance, which is not the intent for this measurement (Dormann et al. 2009).
Ecology Example	Developed to quantify a species' relevance across all of its partners (Bascompte, Jordano, and Olesen 2006, Vázquez et al. 2007).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	If $p_{ij} = \frac{a_{ij}}{\sum_i a_{ij}}$ where a_{ij} is the weighted interaction between product j and element i, then $s_n = \sum_n p_{ij}$ is the strength of species n
Binary or Weighted	Weighted
Maximum or Minimum Values	N/A

For species strength, ecologists have studied it has a possible sign of specialization, but the higher the value, the higher the relevance a species has to the other level in the system. For the material system, this simply points out which elements are being utilized the most.

Interaction Push-Pull

Ecology Definition	Quantifying the effect of species j on species i and vice-versa. Based on species strength but standardized to fall between -1 and 1. Positive values indicate that a species affects the other level more than the other level affects it (pushes), negative values indicate it is being affected more by the other species (pulled) (Dormann et al. 2009).
Ecology Example	Developed to understand if species was more likely to be affected by other species or if the species would be affecting others (Vázquez et al. 2007).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	See Vázquez et al. (2007) for quantification procedures
Binary or Weighted	Weighted
Maximum or Minimum Values	[-1, 1]

Interaction push-pull, as it is referred to by Dormann et al. (2009), describes how species in one level are affected by the species in the other level. For material systems, this would be quantifying if elemental use is more likely to be dictated by the products using it or if the element is influencing the product. Understanding if elemental use is influencing products could be useful for criticality studies. Given a supply disruption, an element that is "influencing" or "pushing" products could have a more profound impact than if the element is being "pulled" by the products. Still, it is not clear what the implications of this measure would be and warrants further study.

Nested Rank

Ecology Definition	Nested rank is a measure of generalism that ranks species by their nestedness (see Nestedness). High generality is indicated by lower ranking, whereas low ranking is indicative of more rare species (Dormann et al. 2009).
Ecology Example	Proposed by Alarcón et al. (2008) who analyzed plant-pollinator networks and found nested rank to be relatively unchanged over time. They note that several studies have shown plant-pollinator networks to be highly asymmetric with few specialists interacting with several generalists, this pattern of several rare with few abundant is their explanation for unchanged ranking.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	Network is rearranged based on maximum nestedness
Binary or Weighted	Binary
Maximum or Minimum Values	[1, S]

Nested rank is simply the rank of nestedness per species in the web, again indicating generalists versus specialists. See discussion related to nestedness for material system implications.

Paired Differences Index (PDI)

Ecology Definition	Another index for specialization and generalism (Dormann et al. 2009). Where 0 indicates generalist and 1 indicated specialists. This is a generalization of resource range (see Resource range).
Ecology Example	This index was recently proposed by Poisot et al. and is based on interaction pairs (Poisot et al. 2011, Poisot et al. 2010)
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	See Poisot et al. (2010) for derivation.
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, 1]

Paired differences index (PDI) is another measure for specialization versus generalization (Dormann et al. 2009). If only binary data is available, Resource range is recommended in place of PDI. Poisot et al. (2012) examined these various indices for factors that may affect their outcomes such as incomplete sampling (a common issue with real ecological networks). They use the species specificity index to quantify the variability in species' interactions. These are fairly new measures and very few studies exist, so it is unclear what benefits they provide over other specialism measures, particularly with respect to a material system.

Resource Range

Ecology Definition	Resource range is a binary estimation of specificity based on exploited resources (Poisot et al. 2012). If result is 0, all resources are exploited versus 1 where no resources are exploited (Dormann et al. 2009). Resources refer to the species that is being "consumed" in the relationship.
Ecology Example	Proposed by Poisot et al. (2012) and used as part of an evaluation for measures that indicate specialism.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	See Poisot et al. (2012) for derivation and discussion.
Binary or Weighted	Binary
Maximum or Minimum Values	[0, 1]

Species Specificity Index

Ecology Definition	Species specificity index is a measure of variability in a species' interactions (Dormann et al. 2009). Low variability is close to 0, while high variability is near 1. Will also yield high values if species is very rare.
Ecology Example	Proposed by Poisot et al. (2012) and used as part of an evaluation for measures that indicate specialism, this measure specifically is related to the variability in a species interactions, but is sensitive to "singleton" species (Dormann et al. 2009).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	See Poisot et al. (2012) for derivation and discussion.
Binary or Weighted	Binary
Maximum or Minimum Values	[0, 1]

Ecology Definition	Similar to species strength, but extended to reflect both how common the species is and whether or not it is specialized (Dormann et al. 2009). High values indicate specialists, but only when the upper level is also specialized, but abundant generalists will also produce high PSI (Dormann 2011).
Ecology Example	Dormann (2011) points out that pollinators are more important when they are both common and specialized.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	$PSI_j = \sum_i (p_{ij} \cdot p_{ij}^{\beta})$, where p_{ij} is defined as in Species Strength and β adjust for how many time a "pollinator" visits a plant before it becomes pollinated and is usually unknown and set at $\beta = 1$ (Dormann 2011)
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, 1]

Pollination service index is the sum of the product of two components of the ecological network: 1) "dependencies of the pollinator (representing their specialization)," and 2) "dependencies of the plant (representing the importance of each plant species for each pollinator)" (Dormann 2011). In Dormann's study (2011), the plants reflect the lower level or "elements" in the material web, and the pollinators, the upper level or "products." This metric is interesting for criticality because for any given element it combines how specialized the element is (possibly indicating it plays an important functional role) with its importance for the products. This combination is reflective of existing criticality metrics, but instead of focusing on various environmental factors (political stability, recycling rate, etc.), it measures the importance to the system only. Therefore, for the material system, this could be a measure of elemental importance to the network, and for criticality, where most important elements would have impact if given a supply disruption.

Node Specialization Index (NSI)

Ecology Definition	Node specialization is another measure of specialization that is based on path length (actually the geodesic distance) between any two upper level species (Dormann et al. 2009). High values indicate specialization and is determined based on nearby species in the lower level (Dormann 2011).
Ecology Example	NSI is a new metric, proposed by Dalsgaard et al. (2008), that has not been fully evaluated to understand how it responds to true specialization (Dormann et al. 2009).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	$NSI_i = \sum_{i<j}^{n} \frac{d_{ij}}{n(n-1)}$ where d_{ij} is the geodesic distance between each species in the lower level with every other species in the lower level
Binary or Weighted	Binary
Maximum or Minimum Values	$[1, \frac{N_n}{2}]$ where n is either i or j

Node specialization index is used mainly in instances where weighted data is not available. For this reason, and several others outlined in their work, Dormann (2011) suggests using PSI or d' over NSI as a specialization measure. It also requires translation from two-mode to one-mode, which others have pointed out may not be the best way to truly evaluate the system (Opsahl 2007).

Fisher's Alpha and *Partner Diversity*, although calculated at the species level, are both discussed in the network level metrics. Again, Fisher's alpha is not available to this work due to the need for "exact" species counts for interaction weights.

Ecology Definition	Effective partners is essentially Shannon diversity raised to the power e, which converts the value into an "effective number of partners" directly translating the value into units of species (Dormann 2011, Dormann et al. 2009, Jost 2006).
Ecology Example	Measure of specialization where low values reflect specialization and direct number of species (Dormann 2011).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	$EP = e^{-\sum_{i=1}^{S} p_i(\ln p_i)}$
Binary or Weighted	Weighted
Maximum or Minimum Values	$[1, N_n]$ where n is either i or j

Effective number of partners is another measurement for specialization based on Shannon diversity. See other metric discussions for specialization implications for criticality. The major advantage that effective number of partners has over other specialization metrics is that its units are in number of species.

Proportional Generality

Ecology Definition	Proportional generality is the weighted version of normalized degree which measures the number of links with respect to potential links (from level to level) (Dormann et al. 2009).
Ecology Example	Examined along with other specialization/generalization metrics and found to have low correlation with other metrics and be relatively unbiased (Fründ, McCann, and Williams 2015).
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	From the bipartite package: "'Effective partners' divided by effective number of resources ('logbase' to the power of 'resource diversity'; which is calculated from high.abun/low.abun if provided, and else from marginal totals)" (Dormann, Gruber, and Fruend 2008). Resources refer to the species being "consumed."
Binary or Weighted	Weighted
Maximum or Minimum Values	Can be larger than 1 when a species "selects a balanced diet" (Dormann et al. 2009).

Proportional generality is similar to normalized degree, but accounts for interaction weights. See discussions around normalized degree and degree for criticality implications.

Proportional Similarity

Ecology Definition	Proportional similarity measures specialization based on dissimilarities between "resource use" and resource availability (Dormann et al. 2009). Again, resource refers to the species being "consumed."
Ecology Example	Proposed and studied by Feinsinger et al. (1981) for measuring niche breadth.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	See Feinsinger et al. (1981) for derivation.
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, 1]

Proportional similarity, as described by Feinsinger et al. (1981), highlights a new approach to specialization and generalization. Here, these concepts are described as niche breadth. Niche breadth is tied closely to evolutionary ecology and essentially refers to the diversity and patterns of feeding. They point out that "if two populations have access to the same resource base, then the population whose members as a group tend to use resources in proportion to their availability (discriminate less among resource states) has a broad niche relative to a population whose members as a group tend to concentrate on items in some resource states and to bypass items in others" (Feinsinger, Spears, and Poole 1981). This is where proportional similarity comes in, as it is calculated by comparing frequency distributions of consumed resources with the frequency distributions of the resources available for consumption. This seems to be useful for the material system, by comparing how elements are consumed to the potential for consumption, but it assumes that all products would be interested in "consuming" all elements, which seems to be a serious disconnect between the ecological applications of some metrics and the material system.

	d'
Ecology Definition	d' is a measure of species specialization where high values are indicative of specialization. It is a degree measurement, so it is based on potential. Values of 0 are indicate a "perfect opportunist," while 1 is a "disproportionate specialist" (Dormann 2011, Dormann et al. 2009).
Ecology Example	Recently developed by Blüthgen et al. (2006), used to measure degree of specialization at the species level. See discussion below about sensitivities.
Industrial Ecology Example	N/A
Network Example	N/A
Equation/Calculation	This measure was proposed by Blüthgen et al. (2006) and calculation is discussed simply by Dormann (2011), see these sources for calculations.
Binary or Weighted	Weighted
Maximum or Minimum Values	[0, 1]

For the material system, d' measures the expected degree of specialization and is based on the number of products that utilize an element. Again, the more specialized an element becomes, the more likely it is important for a specific function and given supply disruption could cause price spikes for its products. It is important to note that ecologists have found d’ to be very sensitive to rare species (Blüthgen, Menzel, and Blüthgen 2006, Dormann 2011). Typically, if d’ is exactly 0, then a rare element happens to visit a common product, and if d’ is near 1, the rare element visits a rare product.

2.5. Metric Selection

Methodology for metric selection took several steps. All metrics available via the bipartite package were calculated for the rare earth system (as applicable, some metrics could not be calculated), but it was important to adequately evaluate each metric to ensure appropriate selection and avoid cherry-picking. First, metrics were evaluated for criticality application based on historical precedence. Some metrics were chosen for their popularity in ecological literature and industrial ecology literature. This is helpful for comparing and contrasting values between the systems. Then, based on simple descriptions, metrics of interest for criticality were selected. These metrics may not have direct translation, but highlight features of interest for critical materials. Metric descriptions also highlighted metrics that could be eliminated on the basis that they could not be calculated for the bipartite network, namely Fisher’s alpha. Finally, in order to eliminate some of the redundant metrics, useful or not, correlation and cluster analysis was conducted for the metric results.

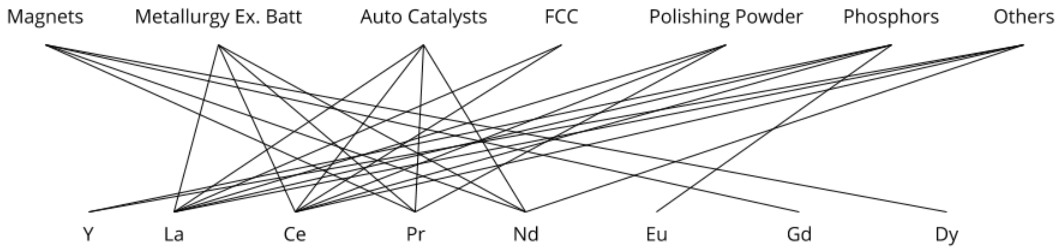
For redundancy analysis, correlations were generated using Spearman’s rho. Cluster analysis was conducted for the correlations using Spearman’s squared to be consistent with analysis by Dormann et al. (2009). Cluster analysis and correlations are important for highlighting where specific metrics are likely to duplicate efforts. Many of the metrics analyzed are measuring similar network properties (e.g. nestedness, diversity). It is also important to retain as much of the data variation as possible, which is why it is critical to select metrics across the clusters.

Ecologists have had the benefit of studying and adapting these measures for several decades, but using these measures for critical material systems is new, so it is important now to capture the basic concepts and tweak metrics later. This is mentioned for the sake of sometimes choosing simplistic or precedent metrics over newly developed or “improved” metrics. Overall, these analyses were conducted to highlight where metrics were measuring similar properties, potential relationships, and independent measures.

3. RESULTS

Data for each country and year produces graphs for both a bipartite network and a typical network. Examples of these results are shown for the U.S. 2000 rare earth use data, Figure 5. A sample of the data matrix for this network and of those analyzed can be found in the supplemental information of Du and Graedel (2013). Bipartite networks for each country for 1995 and 2007 are shown in Appendix A. Although simplistic, there is information to be gleaned from these graphs, particularly the bipartite network. From Figure 5a, it is evident that La, Ce, and Pr are used in several of the products for the United States in 2000. Conversely, Eu, Gd, and Dy are utilized by the fewest number of products. For the product perspective, FCC utilized the least number of elements, while phosphors, magnets, auto catalysts, and metallurgy (except batteries) required the largest number.

a. Bipartite graph



b. Network graph

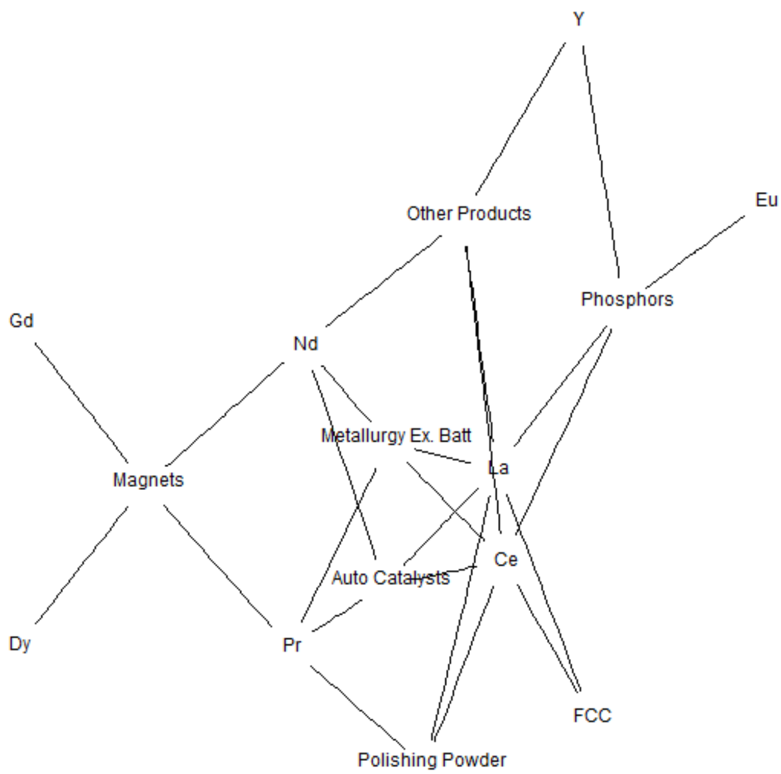


Figure 5. Sample graphs for 2000 U.S. rare earth element use.
Represented as a. Bipartite graph, and b. Network graph (Du and Graedel 2013). These graphs exemplify the visual inspection process of studying systems, where the bipartite graph is much easier to gain information for this type of system.

Information obtained from visual inspection of the bipartite network is not as obvious in the typical network graph in Figure 5b. Overall, elements that are utilized by a larger number of products seem to be more critical, but without considering the magnitude of consumption, abundance (or availability), and demand from products, that is not necessarily the case. An example of where this would be an issue is if an element were used by several products, but in very small quantities and the production of the product was also low. From the graph perspective, it would appear the element was in very high demand, but it could be an abundant element that was in low demand by several products, which does not necessitate criticality. An example is cerium. If it is used in several products (polishing powders, glass additives, catalysts), but in small quantities, and those products have a small market, it might seem critical or important because it is highly connected, when actually, its demand is low.

Fortunately, this visually highlights areas for future criticality inspection. Products vulnerable to supply risks likely use or rely on few elements. Ecologically speaking, this is considered specialization, where a species is consuming or relying on few other species. Here, a specialized product is relying primarily on one or few elements versus a generalist which would utilize many different elements. Elements used by many products will impact a larger number of products given a supply risk and/or price increase. Without taking into account the magnitude and the network structure, it is difficult to draw definitive conclusions about the system from the network diagrams alone, therefore various bipartite metrics are analyzed to describe the system.

3.1. Selected Metrics

Results for all metrics are shown in Appendix B. While all metrics were analyzed, metrics with historical precedence, interest to criticality applications, and non-redundant metrics were chosen for further discussion.

3.1.1. Network-level

At the network-level, connectance, cluster coefficient, Shannon diversity, and interaction evenness are included for prevalence reasons. Connectance, Shannon diversity, and interaction evenness are common to food web analysis and industrial ecology applications. Fisher's alpha is not included because it cannot be calculated for these systems without species' counts in integer form. Compartment diversity is also not included because none of the systems analyzed contained more than one compartment, thus, compartment diversity is actually equal to the diversity of the network. Because there is only one compartment for the networks analyzed, for this specific analysis, we can also eliminate the metric "number of compartments." In fact, cluster coefficient is similar in concept to number of compartments, but without actual breaks in the network, so the overall concept is still quantified with the metrics selected. Specialization asymmetry, of the network-level metrics, is of interest for criticality. Values of specialization asymmetry indicate specialization of the product-level, which indicate whether the products are utilizing few or many elements. At the system level, this is key, because highly specialized systems can be more vulnerable to minor changes. For product markets that are highly specialized, this could be troublesome given slight fluctuations in elemental availability. Similar to specialization asymmetry is H_2', a measure of network-level specialization, which is highlighted in the correlation matrix (Figure 6) with a negative correlation of -0.7. A negative correlation makes sense here because H_2' is measuring the specialization of the overall network, so as it increases, both the elements and products would be getting more specialized and the asymmetry between the two levels would decrease. Fortunately, this emphasizes the challenge of network-level metrics. These metrics are high-level and lose the important details and intricacies of the system.

Based on the correlations in Figure 6, Shannon diversity and interaction evenness are highly correlated (0.9). This makes sense because the calculation for interaction evenness is based on Shannon diversity. There are also high correlations between nestedness, cluster coefficient, weighted nestedness, weighted NODF, and connectance. Nestedness and cluster coefficient, in particular, are highly correlated (0.9), likely due to their concept similarity. Basically, nestedness cannot exist in the network without clustering or vice-versa. The cluster analysis of the network-level metrics, Figure 7, illustrates some of the metric similarities shown by the correlations. The highest clusters are Shannon diversity and interaction evenness, along with, cluster coefficient and nestedness (both have cor=0.9). Specialization asymmetry and interaction strength asymmetry are similar in that neither of them is very highly correlated with any other metric (aside from H_2' and specialization asymmetry); therefore, these two measures are fairly independent. The cluster analysis shows there are three main clusters and the metrics selected for the network-level span these three clusters. From the first cluster, Shannon diversity and interaction evenness, the second cluster, cluster coefficient and connectance, and the independent cluster, specialization asymmetry. R code and the correlation table are in Appendix D-5 and E respectively.

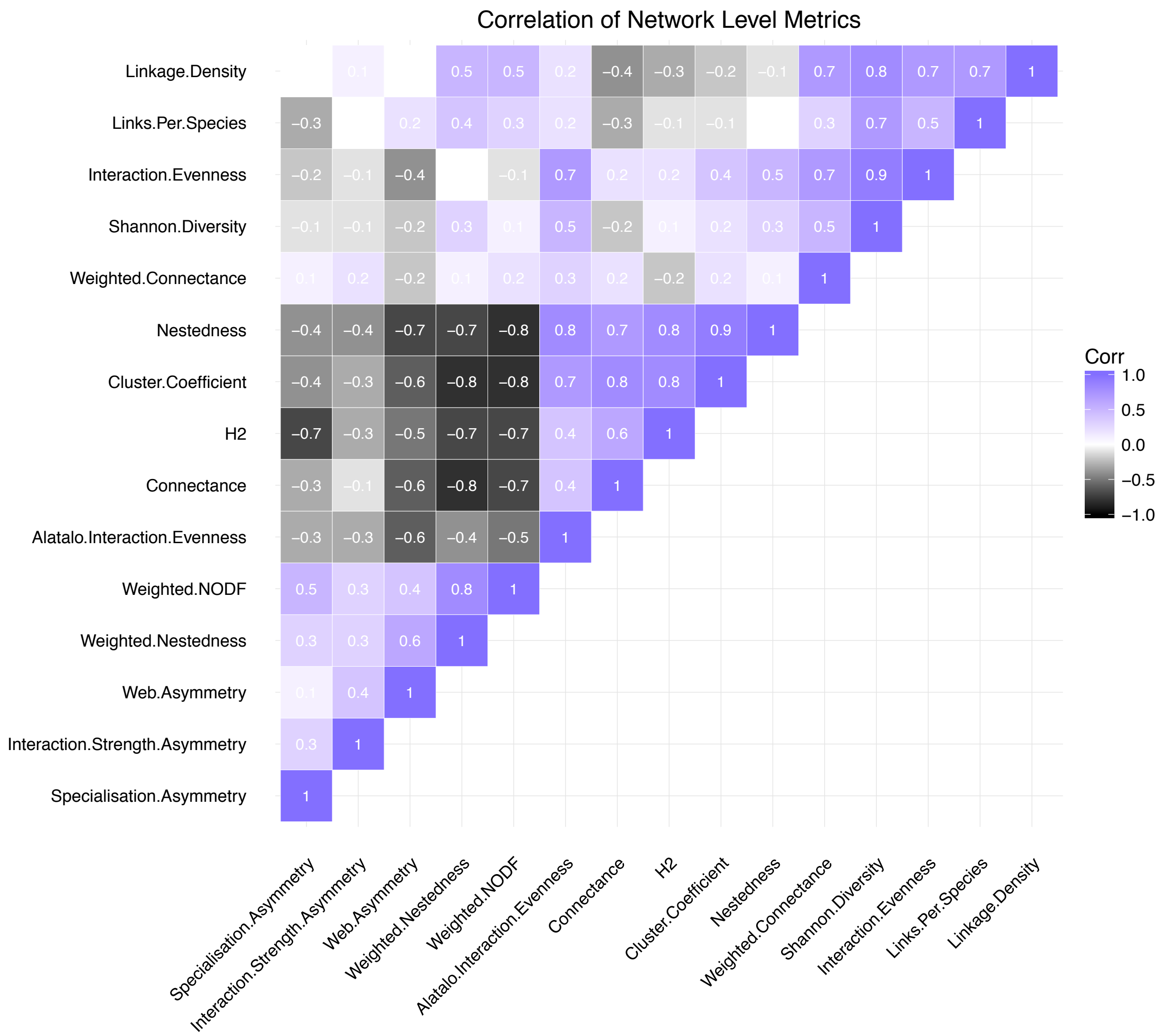


Figure 6. Correlation Matrix for Network-level bipartite metrics.

Excluded metrics include Fisher's alpha, number of compartments, and compartment diversity. Correlation was calculated using Spearman's rho.

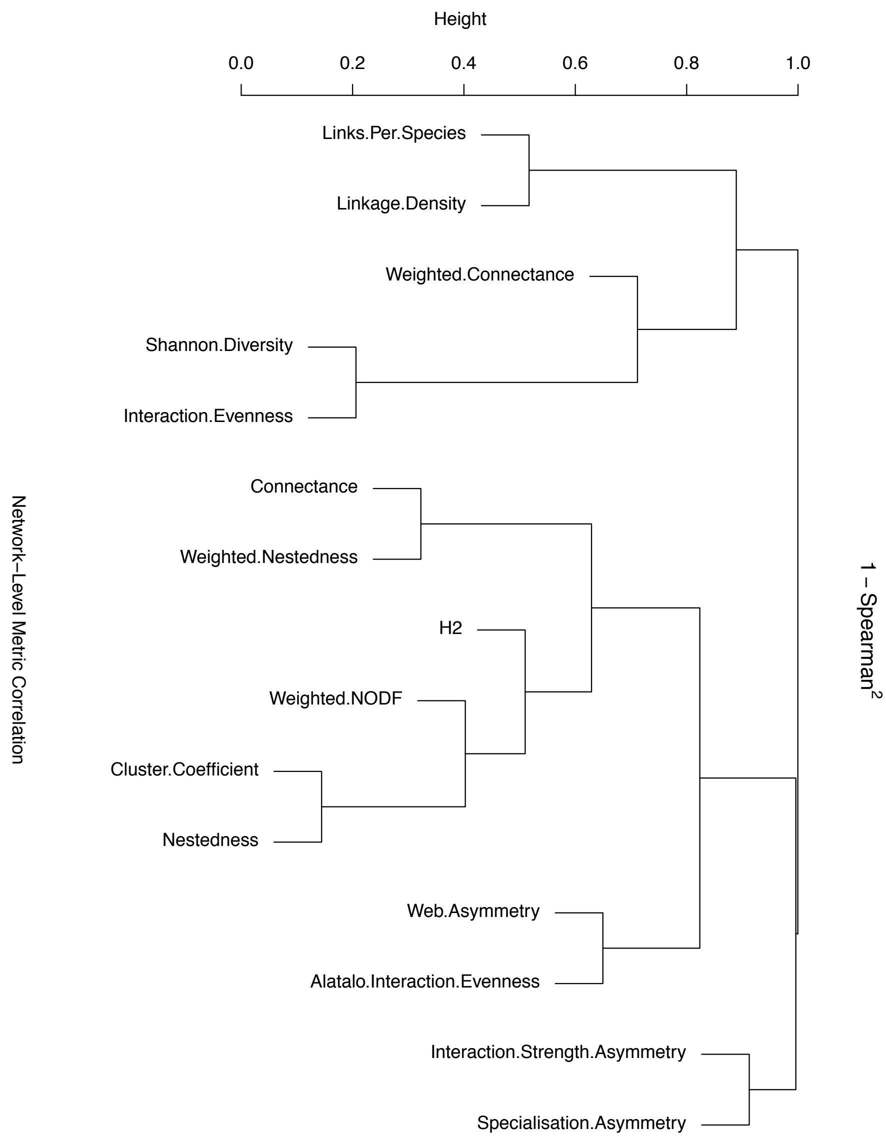


Figure 7. Cluster analysis for the Network-level metrics.
Distance is based on spearman's rank correlation coefficient. Excluded metrics include number of compartments, compartment diversity, and Fisher's alpha.

3.1.2. Group-level

At the group-level, cluster coefficient for both levels (HL and LL) is selected on the basis of historical prevalence. This metric is the same as cluster coefficient at the network-level, so a second layer of analysis is added. None of the metrics at the group-level are unable to be calculated, so no metric is eliminated on that basis. Extinction slope of the upper level is a potentially useful metric in terms of criticality. Extinction slope HL quantifies the products' ability to persist after removal of elements, so it was selected for that reason. Robustness is also a promising measurement for criticality, but it quantifies the area under the extinction slope and was found to have a correlation coefficient of ~1, Figure 8. Partner diversity was highly correlated with generality HL and vulnerability LL (0.9 and ~1 respectively), due to their calculation deriving from Shannon diversity (Bersier, Banašek-Richter, and Cattin 2002). Of these three, vulnerability could be the most useful for criticality, as it highlights the level of importance of the elements to the products. Niche overlap of the lower level is also of interest for criticality studies. In other studies, it proved to show technological overlap, which translates nicely to substitution, a common criticality mitigation strategy.

Group-level metrics cluster analysis, Figure 9, highlights one cluster in particular that constitutes several of the metrics. This cluster contains weighted cluster coefficient LL, mean number of shared partners HL, mean number of shared links HL, extinction slope HL, and robustness HL. This cluster is also obvious in the correlation matrix, as these measures are correlated as either 0.9 or ~1. From this cluster, extinction slope was selected. Cluster coefficient and vulnerability come from the two lower clusters, while niche overlap is pulled from the remaining cluster. Cluster coefficient HL and togetherness HL seem to be the most independent, of which, cluster coefficient will be analyzed.

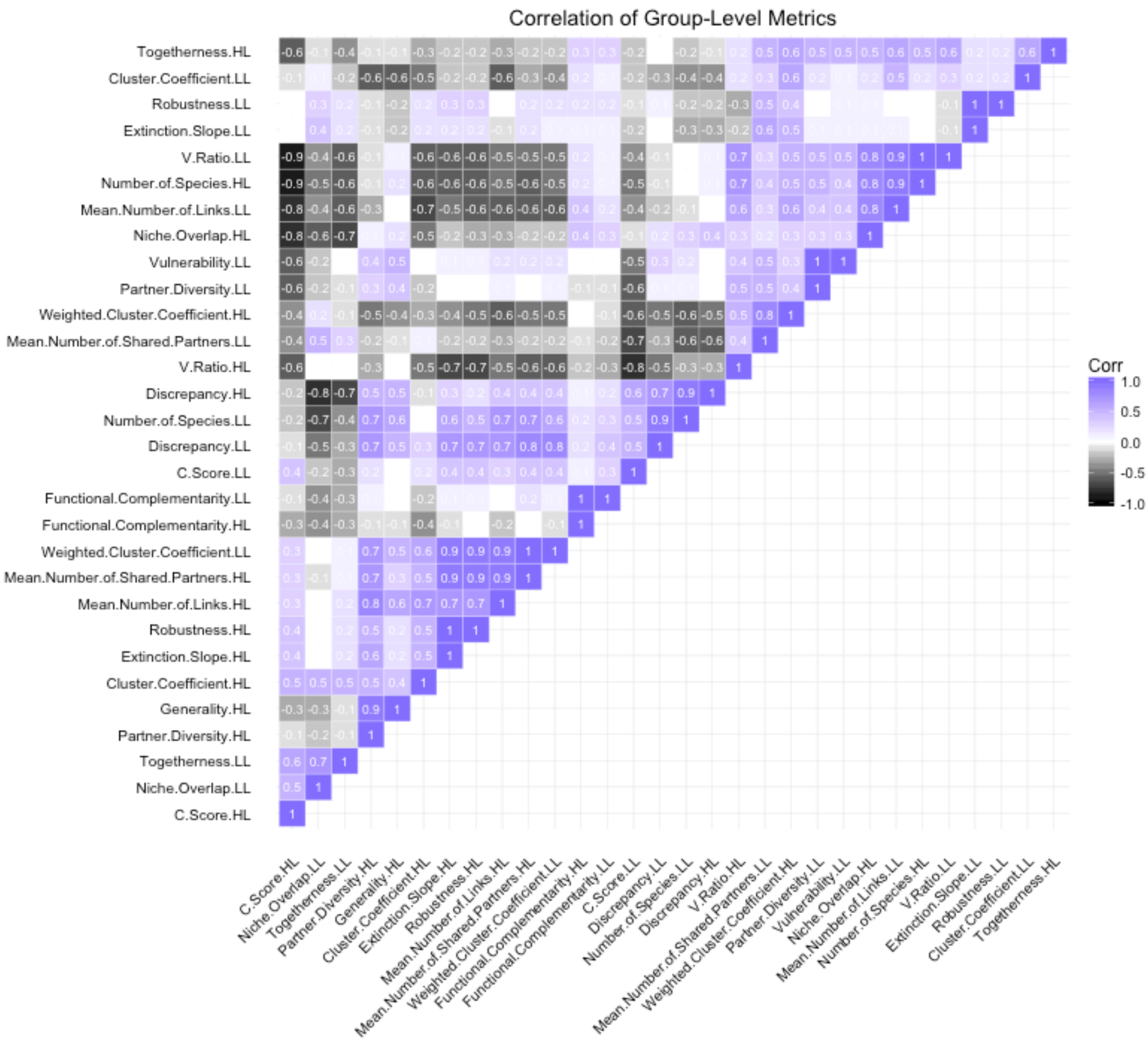


Figure 8. Correlation Matrix for Group-level bipartite metrics.

Correlation was calculated using Spearman's rho. Both higher-level (HL) and lower-level (LL) metrics are included.

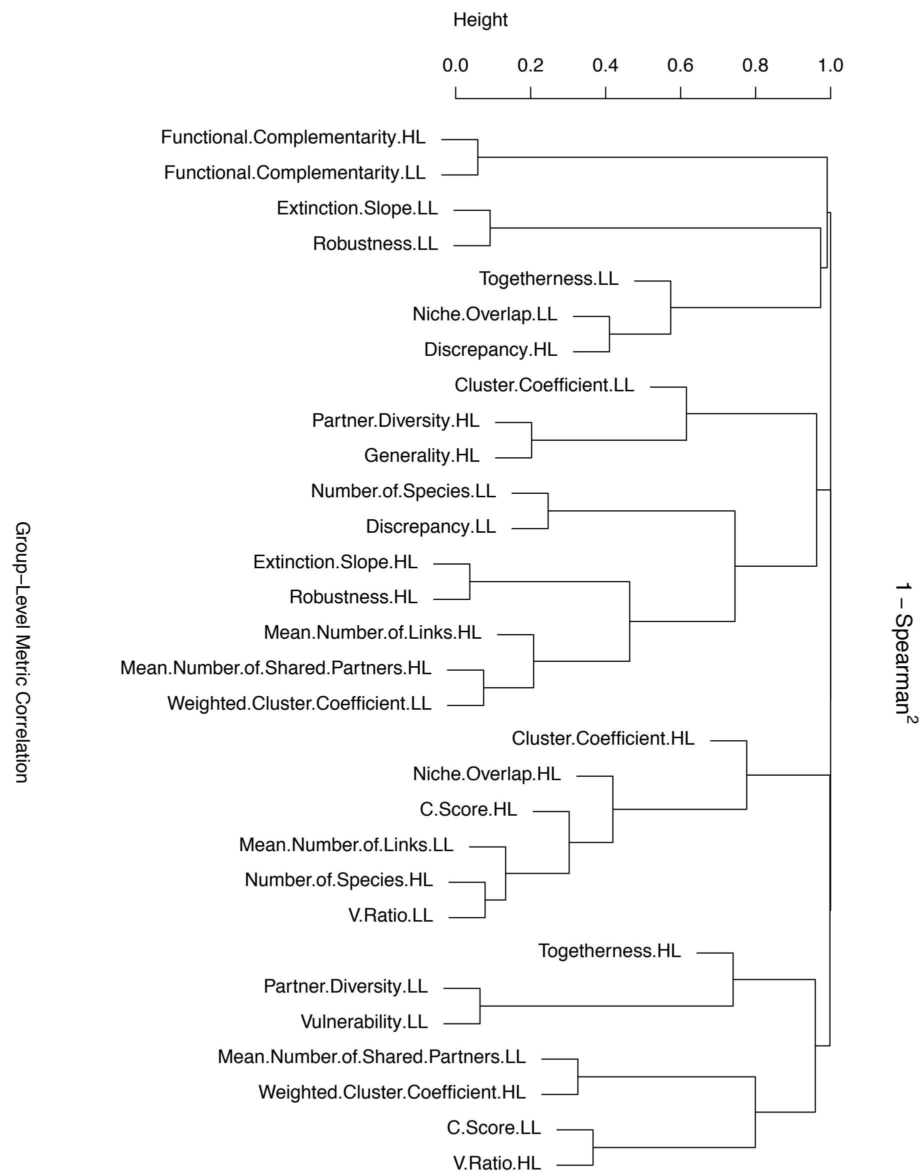


Figure 9. Cluster analysis for the group-level metrics.

Distance is based on spearman's rank correlation coefficient. Both higher-level (HL) and lower-level (LL) metrics are included.

3.1.3. Species-level

At the species-level, normalized degree, weighted betweenness, and partner diversity were selected as metrics of precedence. Normalized degree was selected over degree because it has higher correlations with other metrics. Degree is a common metric for both network analysis and ecological analysis. Betweenness was selected as a representative network centrality measure, and because it quantifies a species' ability to influence others within the network. Weighted betweenness is selected over betweenness because it accounts for the interaction weighting. Partner diversity is based on Shannon diversity, so it gives another layer to the analysis and also is potentially useful for criticality studies by quantifying the importance of an element to the product-level.

Metrics that were selected for potential usefulness for criticality are interaction push-pull, and d' specialization. Interaction push-pull is used to evaluate whether the elements or the products are the most influential in the network, and d' specialization is a fairly independent measure for specialization at the species level, Figure 11. Through discussions on the species-level metrics in the methodology section, it is apparent that much of these metrics are measurements for specialization or generalization. Several others encompass the infamous centrality measures from network analysis (e.g. betweenness, closeness). From the correlations, Figure 10, and the cluster analysis, Figure 11, this is also apparent. Figure 10 illustrates clearly two distinct groups of highly correlated measures. The most independent measures are d', betweenness, and weighted betweenness.

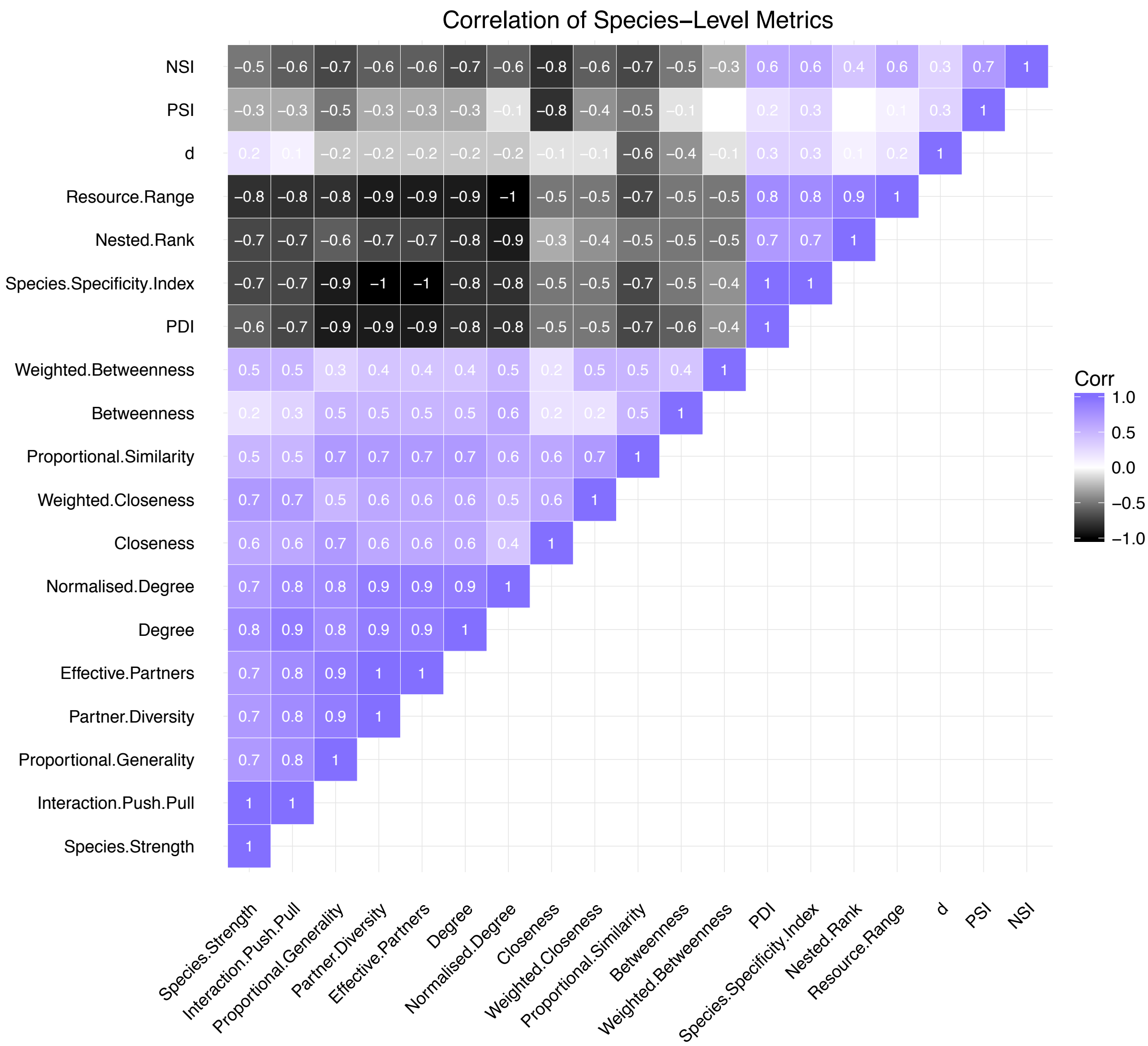


Figure 10. Correlation Matrix for Species-level bipartite metrics.

Correlation was calculated using Spearman's rho. Both products and elements are included in the correlations.

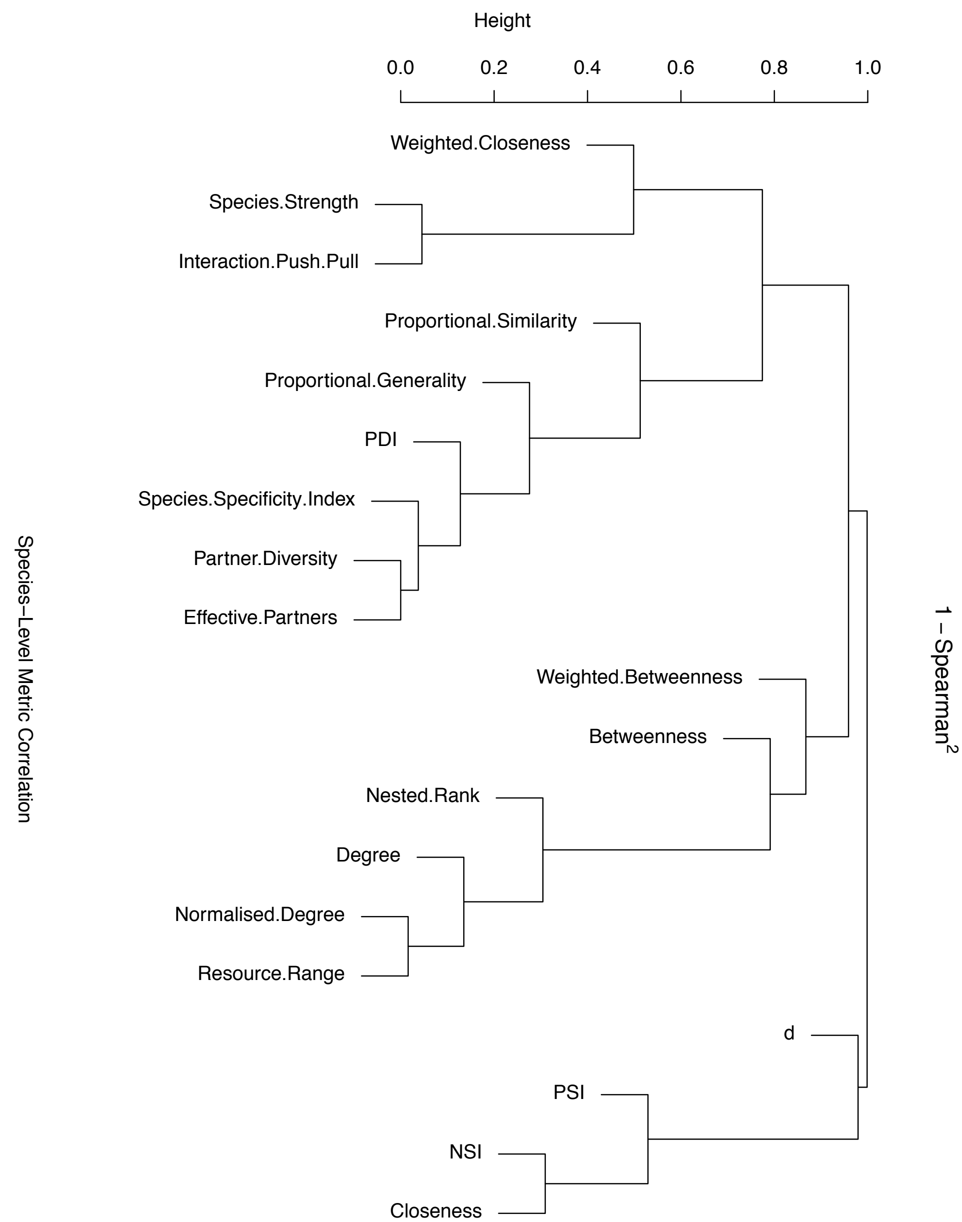


Figure 11. Cluster analysis for the species-level metrics.

Distance is based on spearman's rank correlation coefficient and includes individual element and product "species."

3.2. Metric Results

Of the measures analyzed, those deemed most useful, calculable, and non-redundant, are summarized in table 4 including the ecological and material use description. In this section, the results for these metrics for the rare earth system are described.

Table 4. Summary of selected metrics and descriptions for their applications in various networks and potential meaning for the material network.

Metric	*Level*	*Ecological/Network Description*	*Material Network*
Cluster Coefficient	Network, Group	High clustering is multiple groups of interconnections that are weakly linked to other groups of interconnections. Networks with high clustering are typically robust to random attacks, but vulnerable to targeted attacks.	Potentially an indicator for efficiency of use and transport, and likely indicator of robustness to random removal or changes in elements.
Shannon Diversity	Network	Used to describe potential stability of the system and has been studied to examine changes in diversity due to environmental losses.	Could be used in studies to understand how external changes, elemental supply disruption, for example, affect overall diversity.
Interaction Evenness	Network	Highlights systems where a species or combination of species is dominating.	Highlights systems that are relying on a single element-product pair.
Connectance	Network	Measures interconnectedness	
Specialization Asymmetry	Network	Positive values indicate a higher specialization of the higher trophic-level.	Positive values indicate higher specialization of the product-level, signifying that the products are utilizing a decreasing number of elements.
Niche Overlap	Group	Similarity in interactions between members of a species' group.	Similarity in interactions amongst elements or products, potentially measuring substitution relationships.
Vulnerability	Group	Number of upper-level species per lower-level species. System-level importance of lower species to upper species.	Number of products per element. System-level importance of the elements to the products.
Extinction Slope	Group	Robustness (or tolerance) of a trophic-level to extinctions in the other trophic-level.	Using HL, robustness (or tolerance) of the system's products to removal of elements.
d'	Individual (Species)	Describes the degree of specialization.	Expected degree of specialization based on the number of products that utilize an element.
Partner Diversity	Individual (Species)	Measures the importance of a species in the lower trophic level to a high number of species in the upper trophic level.	Increasing values indicate elemental importance to an increasing number of products.
Normalized Degree	Individual (Species)	Measures relative connectedness	
Interaction Push-Pull	Individual (Species)	How much influence upper-level has on lower-level species or vice-versa.	Products being influenced by elements could be vulnerable in criticality situations.
Weighted Betweenness	Individual (Species)	Measure of influence a species has over others, or power to change flow.	Measures influence element or product has over others.

3.2.1. Cluster Coefficient – Network-level

Cluster coefficient is a measurement of average connectance for the elements or products within the entire network. China's clustering coefficient remained under 0.5 for the time period studied, but increased slightly over that time, Figure 12. Japan's cluster coefficient was unchanged and still under 0.5, while the U.S. reached 0.5 in 2000, but saw an overall decrease in cluster coefficient. The drastic change in 2000 for the U.S. is intriguing, but cannot be definitively explained. In 1998, a blocked effluent pipe stopped production at the separation plant in Mountain Pass, CA, the only domestic source for rare earth elements (U.S. Geological Survey 1996-2015). It was expected to reopen, but did not until 2012. Based on other notes from the U.S. Geological Survey reports, it is unclear why the U.S. had such a high cluster coefficient in 2000.

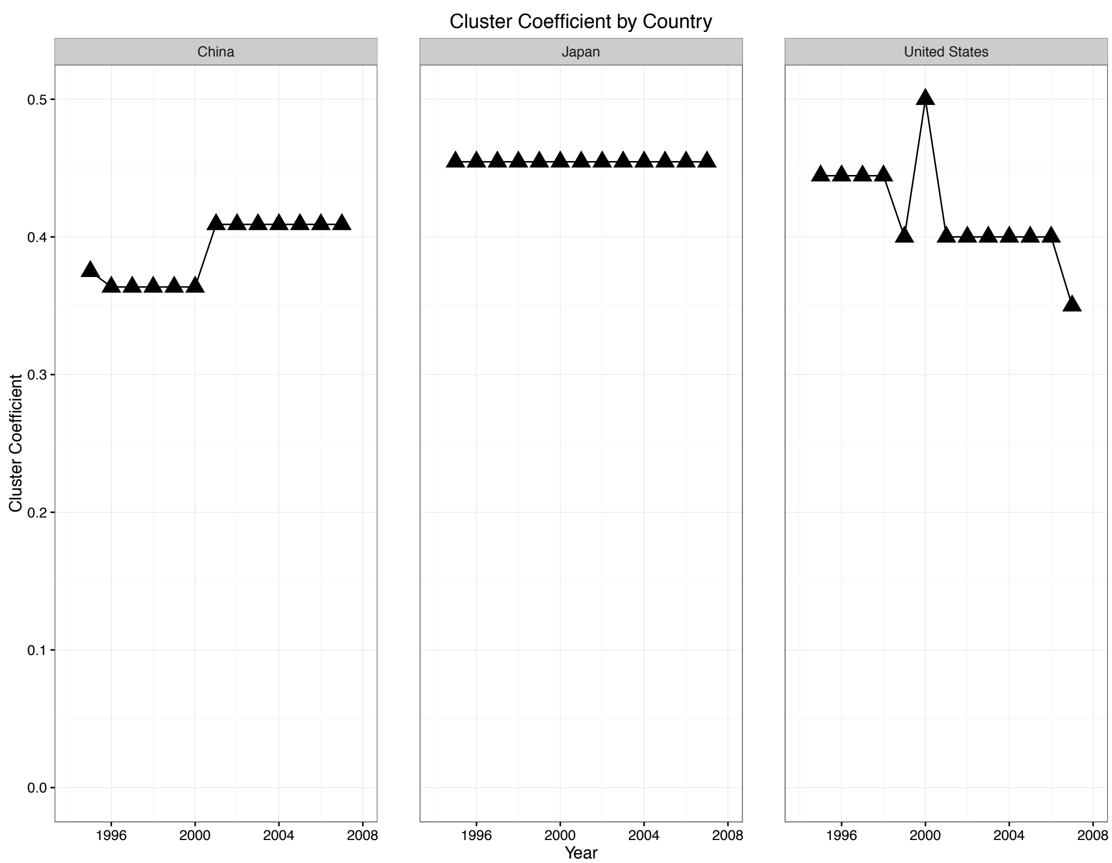


Figure 12. Cluster coefficient network-level results by country and year for the rare earth element material web.

Cluster coefficient was chosen mainly because of its prevalence in network analysis, represented by the variety of networks analyzed and summarized in Table 5. The rare earth material webs fit in with the average of 0.41 cluster coefficient for the other networks, but are low compared to some of the networks, like Movie actors with a value of 0.79. Though their cluster coefficient is comparable, the rare earth networks are much smaller than even the smallest of the other networks (a food web with 134 species). Due to their average cluster coefficients, it is not clear whether the rare earth networks would be robust to removal of elemental species, but it seems unlikely due to their small size.

Table 5. Network properties for various networks compiled by Albert and Barabási (2002) compared to results of the rare earth material systems.

Network	*Size (nodes)*	*Average Degree*	*Cluster Coefficient*
Worldwide Web, site level	153,127	35.21	0.1078
Internet, domain level	3015-6209	3.52-4.11	0.18-0.3
Movie Actors	225,226	61	0.79
LANL co-authorship	52,909	9.7	0.43
MEDLINE co-authorship	1,520,251	18.1	0.066
SPIRES co-authorship	56,627	173	0.726
NCSTRL co-authorship	11,994	3.59	0.496
Math. co-authorship	70,975	3.9	0.59
Neurosci. co-authorship	209,293	11.5	0.76
E. coli, substrate graph	282	7.35	0.32
E. coli, reaction graph	315	28.3	0.59
Ythan estuary food web	134	8.7	0.22
Silwood Park food web	154	4.75	0.15
Words, co-occurrence	460.902	70.13	0.437
Words, synonyms	22,311	13.48	0.7
Power grid	4,941	2.67	0.08
C. Elegans	282	14	0.28
*Chinese REE Network**	16-19	3.51	0.39
*Japanese REE Network**	17	3.41	0.45
*United States REE Network**	15-18	3.40	0.42

**Network analyzed in this work*

3.2.2. Cluster Coefficient – Group-level

Cluster coefficient was also selected for the group-level. For the element group, Figure 13, the cluster coefficients are relatively high compared to the values at the network level and for other networks, as summarized in Table 5. China's elemental cluster coefficient increased in the middle years, but declined again in the later years. Japan was relatively constant around 0.75-0.76, which is slightly higher than China's lower values. For the U.S., it followed a similar pattern as China, but dropped sharply between 2003 and 2004. The drop here could be due to a significant decrease in consumption of rare earths in the U.S. that occurred in 2004 (U.S. Geological Survey 1996-2015). While the cluster coefficients are high for the elements, if high clustering signifies robustness, the elements are not vulnerable to losses in the products, which is what you would expect.

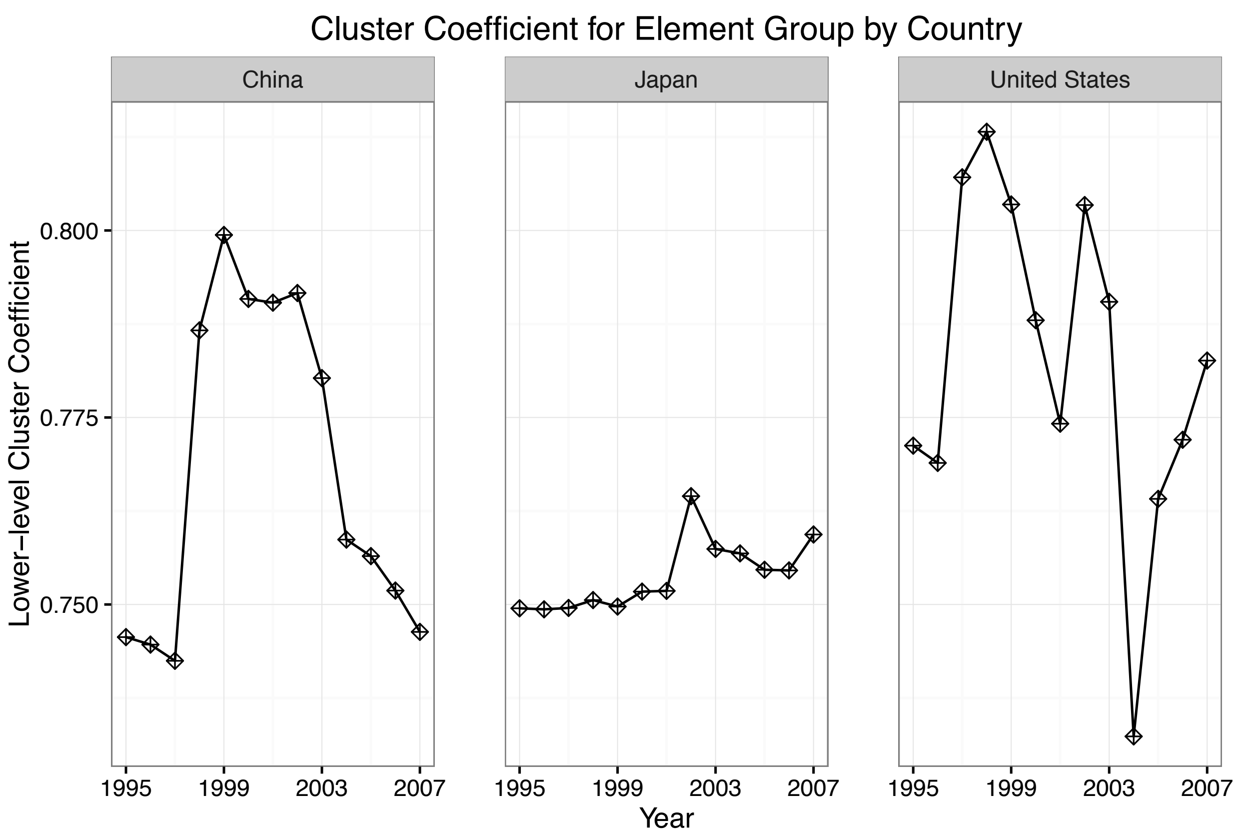


Figure 13. Cluster coefficient for the element level of rare earth element networks from 1995-2007 for China, Japan, and the United States.

For the product level, Figure 14, the cluster coefficients are much closer to the values seen in Table 5 for the rare earth element networks. Here, China's values are increasing for most of the time, while Japan's decrease less-so than China. The U.S. system again seems volatile, but did not change much comparing 1995 to 2007. If increased clustering coefficient signifies robustness, then increasing cluster coefficient of the products would be an improvement in the event that there is a supply risk for an element. Further modeling of these systems and subjecting them to perturbations is necessary to corroborate this thought. If it can be shown that clustering does increase robustness in the material systems, then additional substitution of rare earths for other rare earths would increase the robustness of the products to removal of elements via supply disruption.

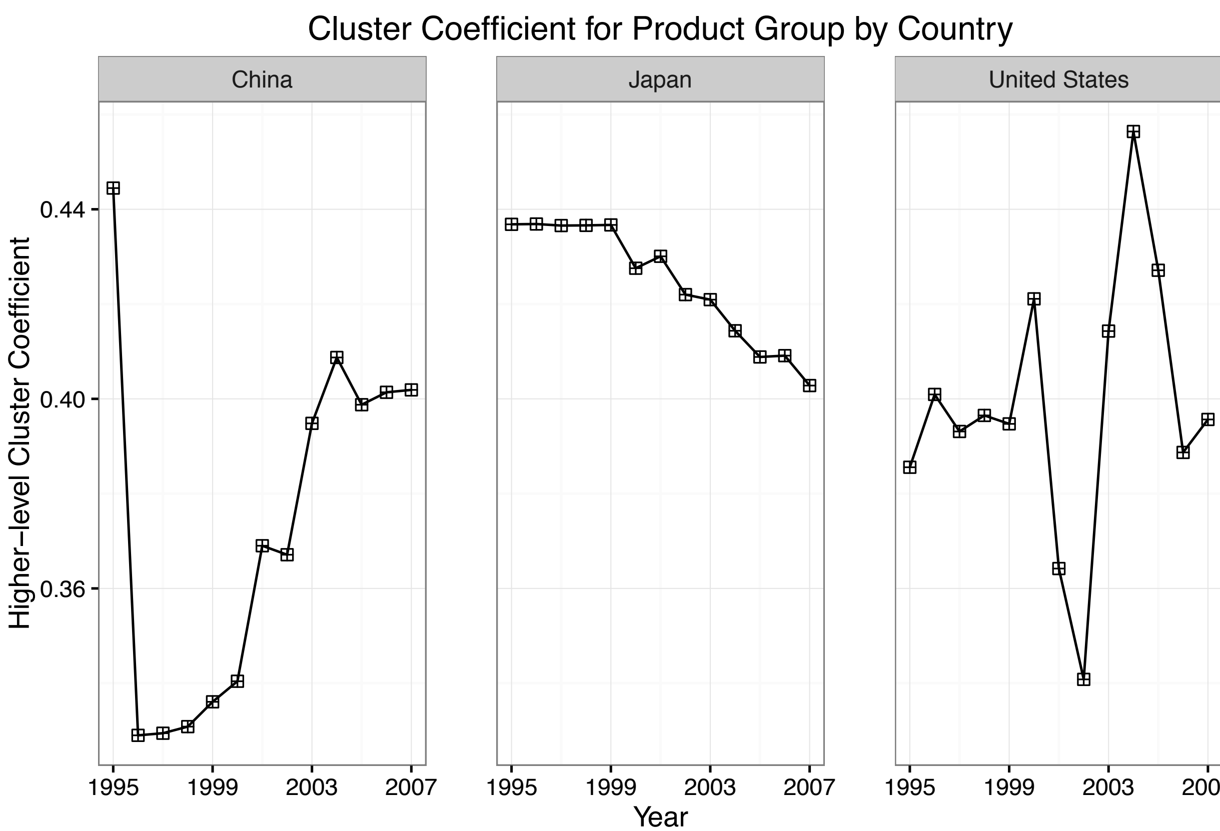


Figure 14. Cluster coefficient for the product level of rare earth element use networks from 1995-2007 for China, Japan, and the United States

3.2.3. *Shannon Diversity*

Shannon diversity was also selected for the network-level because of its persistence in various disciplines. China's Shannon diversity increased over the time studied, and was the most diverse of the three countries. In Japan, the diversity decreased slightly in comparison to the other countries, but was fairly constant. The United States was much more volatile, but did increase over time. The changes in Shannon diversity may be related to the changes in the economy of each country.

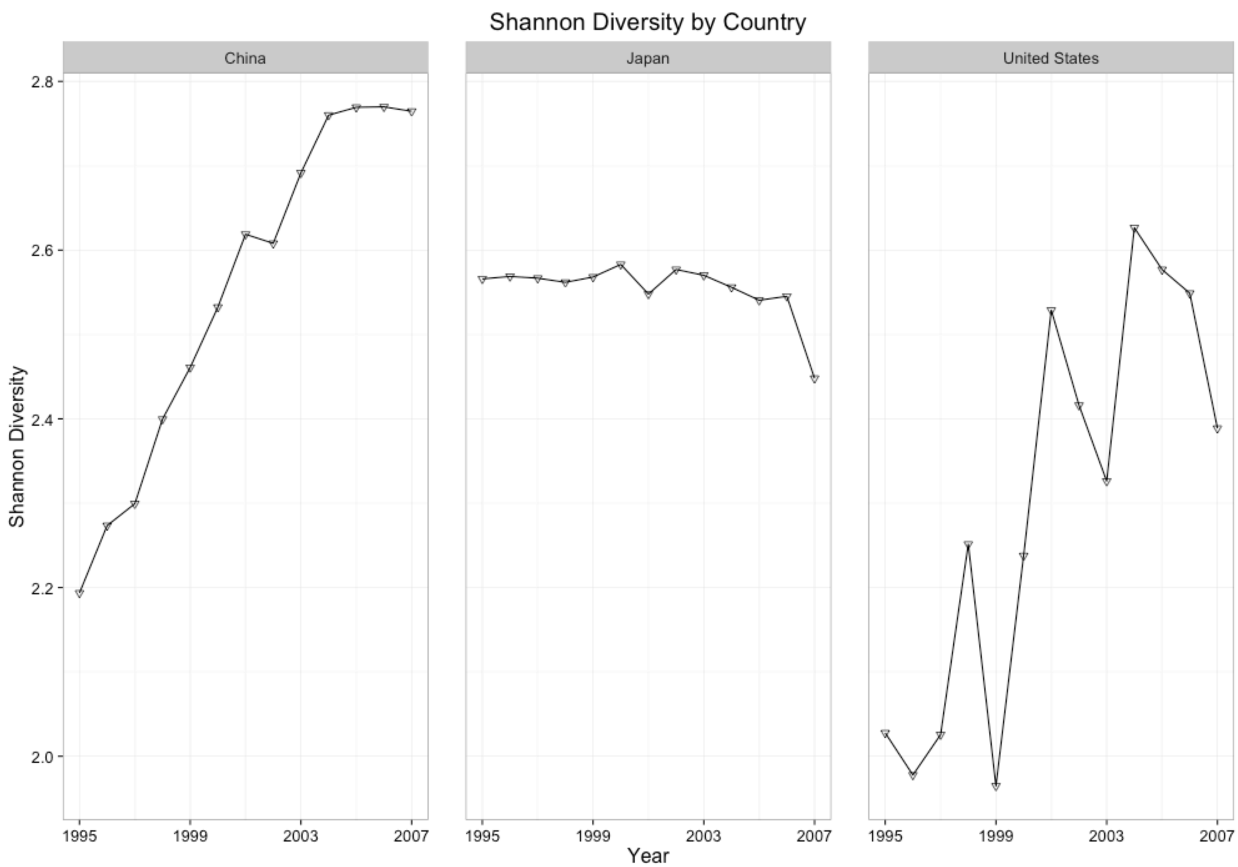


Figure 15. Shannon diversity for the rare earth element networks over time for China, Japan, and the United States

Examining changes in gross domestic product (GDP) for the three countries, Figure 16, highlights that China is still a developing country, though its GDP growth is exponential. Japan's GDP has remained fairly consistent since 1995, while the U.S. has been growing steadily. As a country grows, it makes sense that it would be using more elements in more products, and while these trends align with the trends shown in Shannon diversity, it is only an attempt to explain these results. Further studies are required to determine if a relationship exists between GDP and Shannon diversity.

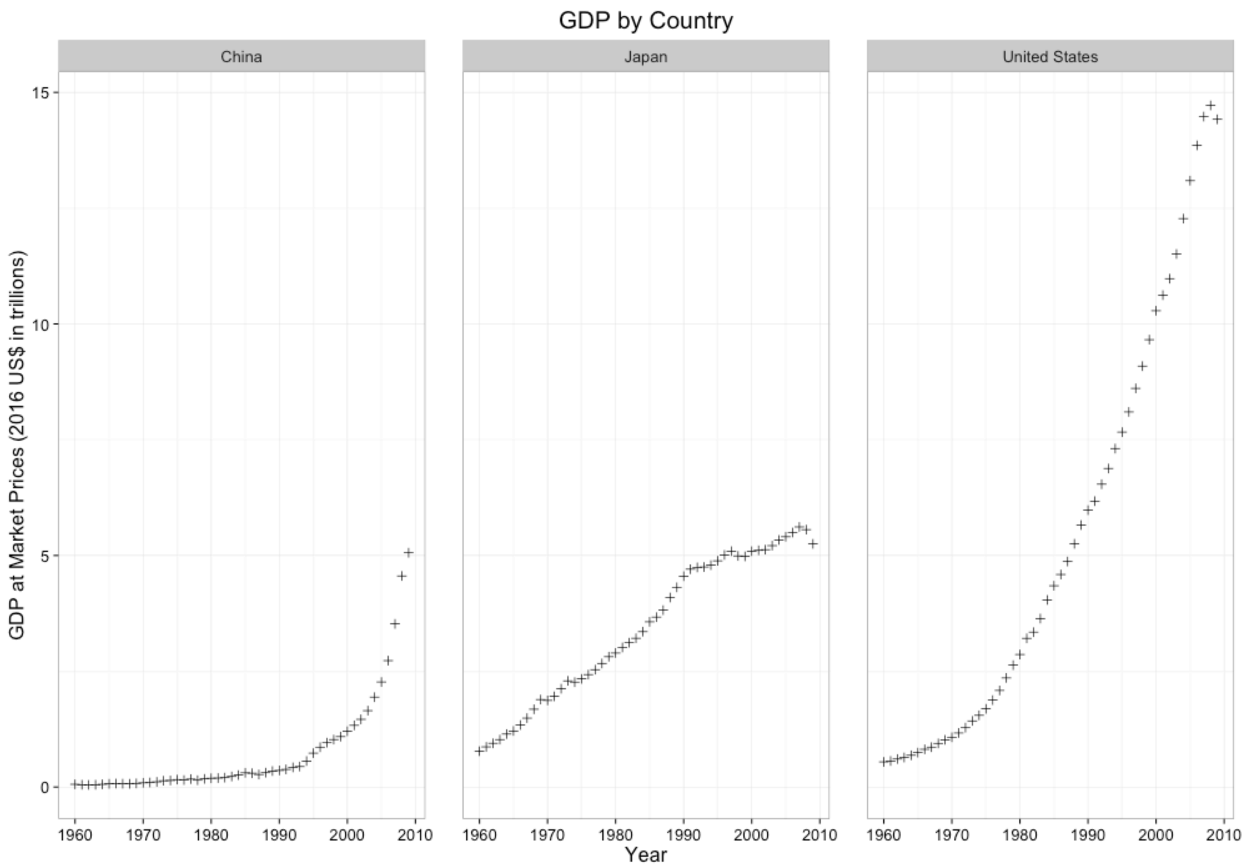


Figure 16. Gross domestic product (GDP) for China, Japan, and the United States in current US$ from 1960-2009.
Data obtained July 2016 from data.worldbank.org (The World Bank 2016)

Given the debate about diversity and stability, and without other material systems for comparison, it cannot be said definitively if these systems are stable. It can be noted that China had the highest diversity of the three countries, in the more recent years, which is corroborated by visual inspection of the 2007 bipartite networks in Appendix A-1.

3.2.4. Interaction Evenness

Interaction evenness was chosen for its continued use in ecological analyses. For the material system, evenness is of interest especially if it is decreasing. When evenness decreases, it means that one or a few element-product pairs are dominating the system. From a criticality stand-point, when the system relies on a single element-product pair, that pair in particular is extremely vulnerable to a supply restriction of the element. Fortunately, for the rare earth element systems studied, evenness was either increasing or stayed relatively the same from 1995-2007, Figure 17. Again, it is difficult to say if these values are actually high or low, but the trends reflect the GDP trends of Figure 16 and also those of Shannon diversity, which was already described by the correlation for these metrics, 0.9, and similarity in calculation. For years of the highest unevenness, inspection of the data matrix could highlight the element-product pairs that were dominating in those years. In the U.S. especially, it is unclear why the data is so volatile, but it may be because it is relying significantly on rare earth imports and so its demand profile is constantly changing.

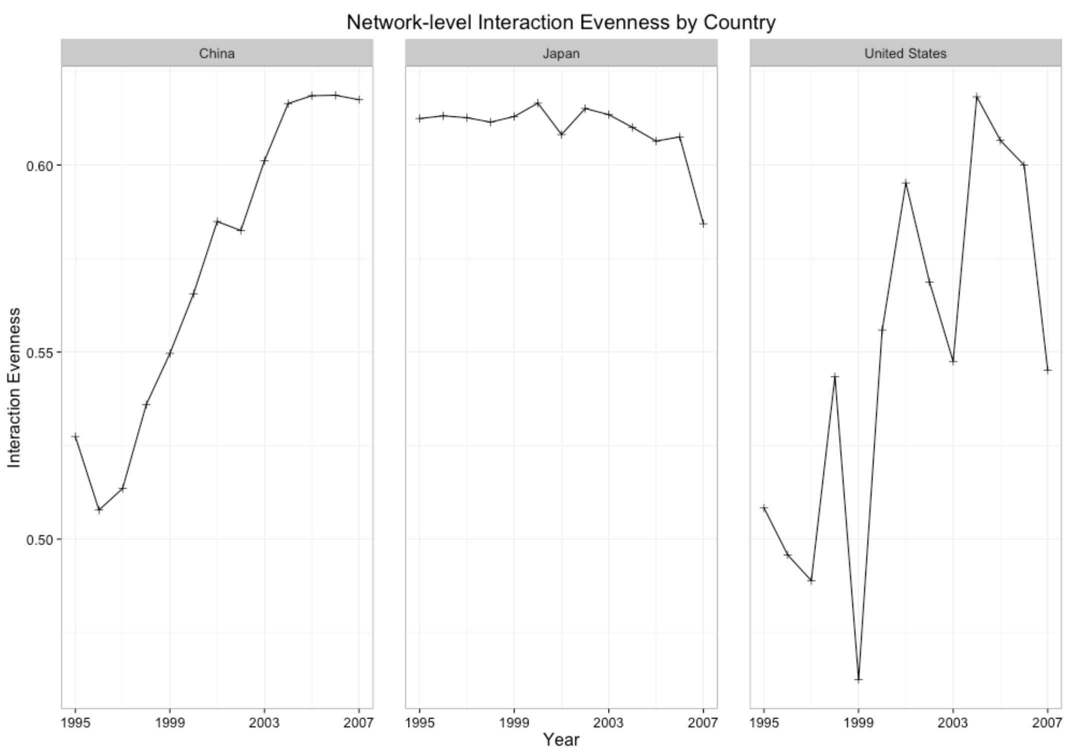


Figure 17. Network-level interaction evenness for China, Japan, and the U.S. from 1995-2007

3.2.5. Connectance

Connectance was also chosen because it has been widely studied. China's connectance, Figure 18, was low compared to the other countries. For the Chinese system, this is a potential concern, as Dunne et al. (2002b) examined the robustness of several food webs to extinctions of various species and noted that webs with low connectance were sensitive from the beginning. Still, this is only speculation, and may be very different for the material system. In order for connectance to be related to its resistance to extinctions or removal of elements, further analysis must be conducted to understand the effects of removal.

Connectance for Japan over the time considered did not change; however, this is not reflective of the actual changes that the web experienced, Figure 18. The number of species and links may not have changed in Japan, but the link strengths varied between years. Little change in Japan's web highlights its mature economy and suggests that it is unlikely to experience significant criticality issues regarding rare earths.

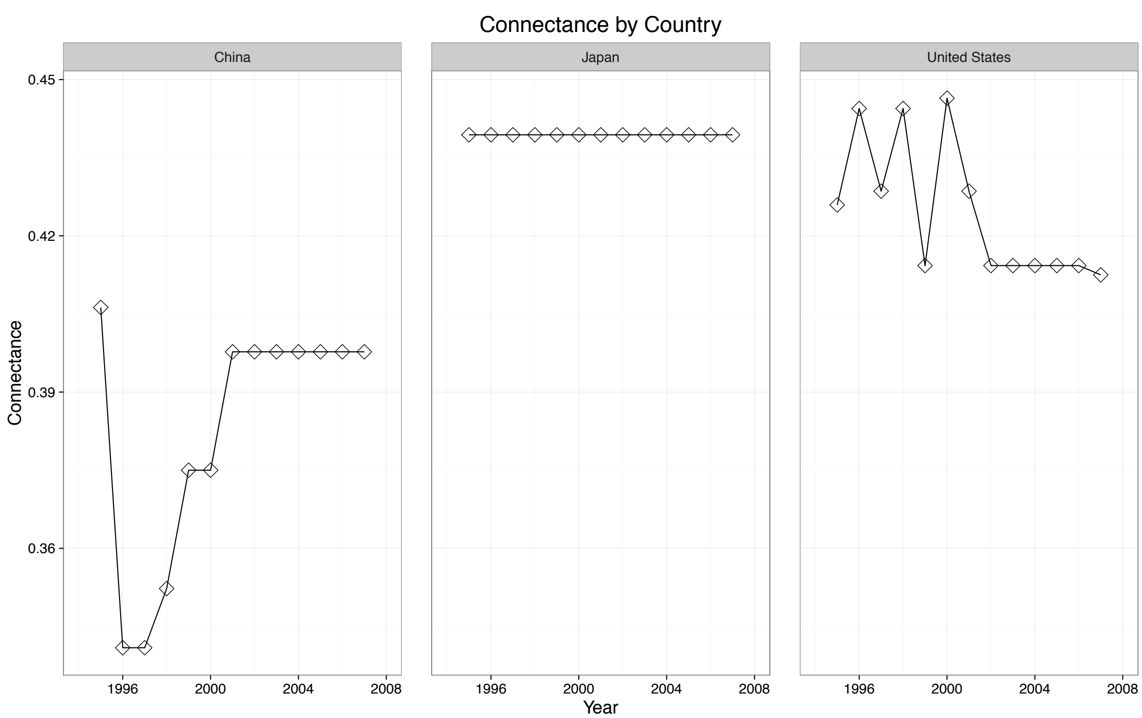


Figure 18. Connectance from 1995-2007 for China, Japan, and the U.S. material networks

Connectance for the three countries was comparable to food webs and industrial parks that have been analyzed,

Table 6. While they found that the industrial parks had higher connectance due to a single highly-connected species such as a power plant, Hardy and Graedel (2002) report that biological ecosystems typically have a connectance of 0.42, which is very similar to the connectance of the RE webs in this study.

Table 6. Summary of connectance values for various systems including food webs and industrial parks.

System	*Scope of Study*	*Minimum*	*Maximum*	*Average*	*SD*
China RE	12 years	0.34	0.41	0.40	0.02
Japan RE	12 years	0.44	0.44	0.44	0.00
United States RE	12 years	0.41	0.45	0.42	0.01
Food Web[1]	16 webs	0.026	0.315	0.11	0.09
Food Web[2]	5 webs	-	-	0.11	0.03
Food Web[3]	50 webs	-	-	0.10	0.04
Eco-Park[4]	1 park	0.31	0.44	0.40	-
Eco-Park[5]	38 years	0.5	0.7	-	-
Eco-Park[5]	18 parks	0.195	0.778	-	-

[1](Dunne, Williams, and Martinez 2002a, b)
[2](Martinez 1992, Dunne, Williams, and Martinez 2002b)
[3](Havens 1992, Dunne, Williams, and Martinez 2002b)
[4](Wright et al. 2009)
[5](Hardy and Graedel 2002)

However, compared to the average connectance of several other food webs, the connectance in the material webs is about four times higher. While low connectance is not seen as desirable in the ecological web, a high connectance may not be beneficial either. If the system is highly connected, it is likely that perturbations will travel more quickly throughout the entire system.

3.2.6. Specialization Asymmetry

Specialization asymmetry is of particular interest to criticality because it highlights the reliance the products have on the elements. China and Japan had decreasing specialization asymmetry and their products are utilizing an increasing number of rare earths (niche is widening), Figure 19, whereas, the United States has an increasing specialization asymmetry, so the products that utilize rare earths are utilizing fewer and fewer rare earths (niche is growing narrower).

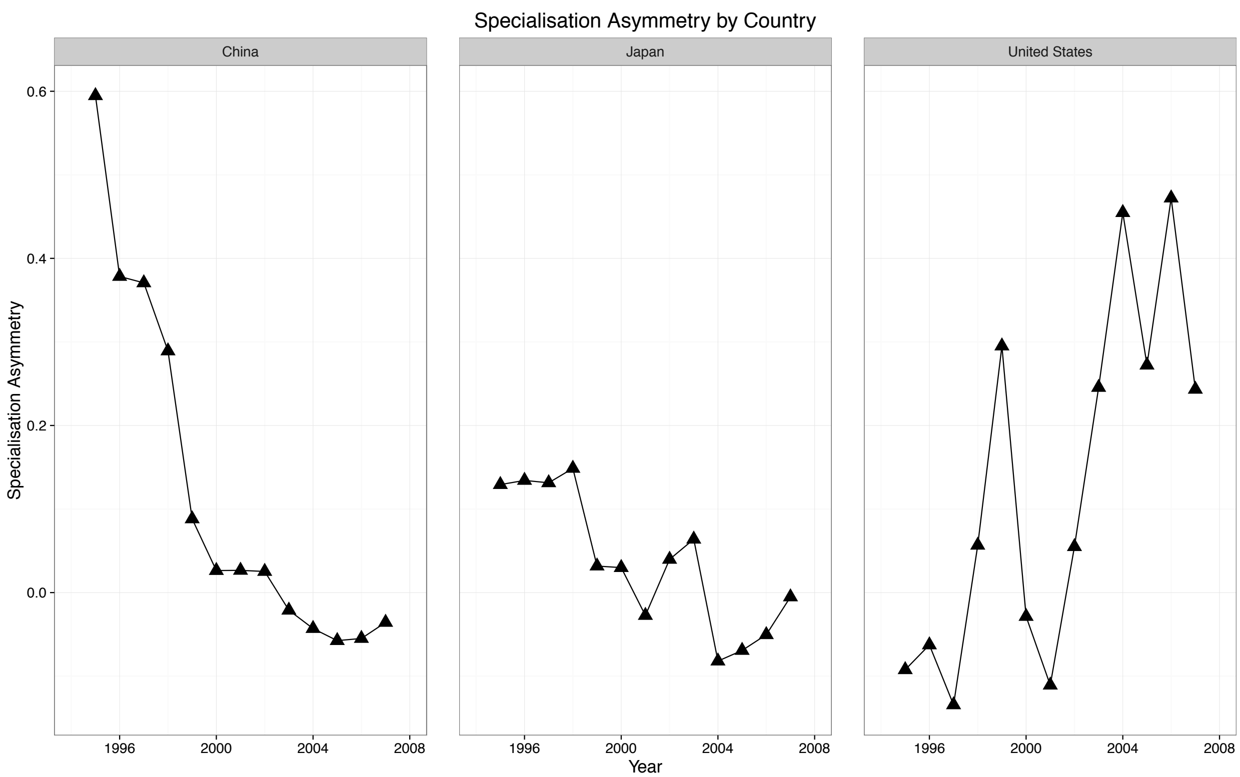


Figure 19. Network-level specialization asymmetry for China, Japan, and the U.S. from 1995-2007

This indicates that China and Japan's products are relying on a larger number of elements and becoming more generalized. Depending on the necessity of the elements for the product function, this is good or bad in terms of criticality. If the necessity to the function is low, relying on a more diverse set of elements can guard against supply issues; however, if the elements are essential for product function, utilizing a greater number of elements with supply issues could increase the price of the product. Depending on the element-product combinations, Japan and China could be increasing the number of elements by substituting rare earths for other rare earths. Substitution is a tactic for reducing criticality, so it must be determined whether or not the elements are necessary or being substituted (U.S. Department of Energy 2011). In the rare earth system, it is not uncommon for the elements to substitute for one another whereas, this might not be the case in a different element system (Nassar, Du, and Graedel 2015).

Specialization asymmetry also indicates the United States rare earth network overall is becoming more specialized, so it is more vulnerable to minor changes, whereas China and Japan's systems are becoming more flexible and adaptable. In terms of criticality, this gives a comparative country perspective on the use of rare earths. As the U.S. is becoming more specialized, it is overall more vulnerable to criticality implications (i.e. supply disruption of elements) than either China or Japan.

In ecology, Blüthgen et al. (2007) show the relationship between specialization asymmetry and web asymmetry as a linear relationship. Basically, if there are more animals than plants, then the plants will be more specialized. If there are more plants than animals, then the animals will be more specialized. In a food web setting, this makes perfect sense because the more abundant the resource, the more selective the species can be with its interactions. This is a prime example of how the rare earth element system differs. Specialization asymmetry and web asymmetry are not related for the material systems analyzed, Figure 20.

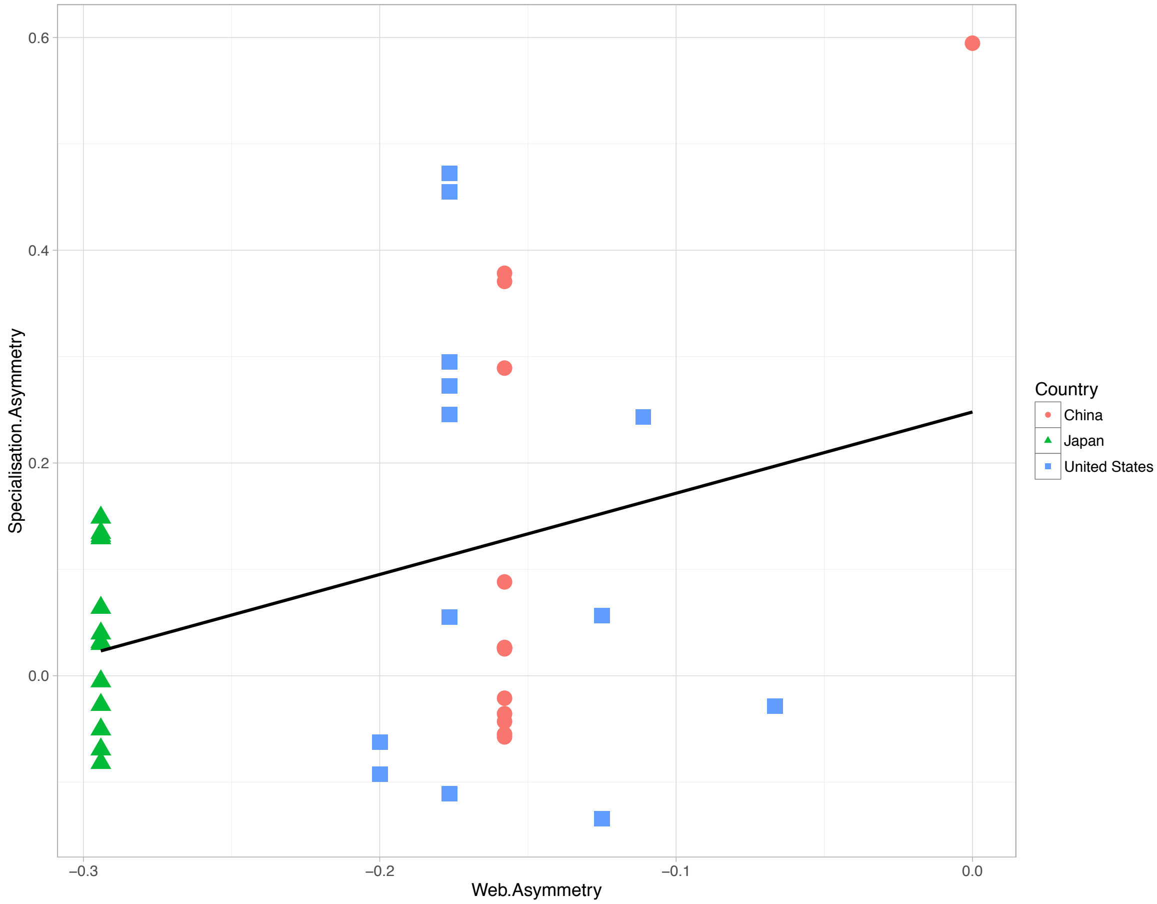


Figure 20. Relationship between specialization and web asymmetry for the rare earth element networks. The relationship between these two measures is non-existent for the material web. For systems where there are more products than elements, the elements are not necessarily going to be specialized. In the ecological system, species are likely to choose the resources they consume based on what is available, but the material system is more complex than that and is based more on physical properties required. This is a significant example of where the metrics and concepts from ecology cannot be blindly applied to the material system.

3.2.7. Niche Overlap

Niche overlap was selected for its potential usefulness for criticality. It measures similarity in interactions; therefore, element groups with high niche overlap are more likely to be utilizing substitution amongst the rare earths. China had the lowest niche overlap for its elements, Figure 21, but seemed to increase over time. Japan had declining, but fairly constant niche overlap. The highest niche overlap is found in the U.S., but again, with variation over time. In the U.S., substitution has been a natural part of mitigating supply disruptions, which may explain why its values are the highest (U.S. Department of Defense 2015, 2013). To truly understand whether or not substitution amongst the rare earths is occurring, examining individual networks would have to be inspected. Permanent magnets utilize Nd, Dy, and sometimes Pr, but usually only very small amounts of Pr, which is added to displace some of the more scarce Dy (U.S. Department of Energy 2011).

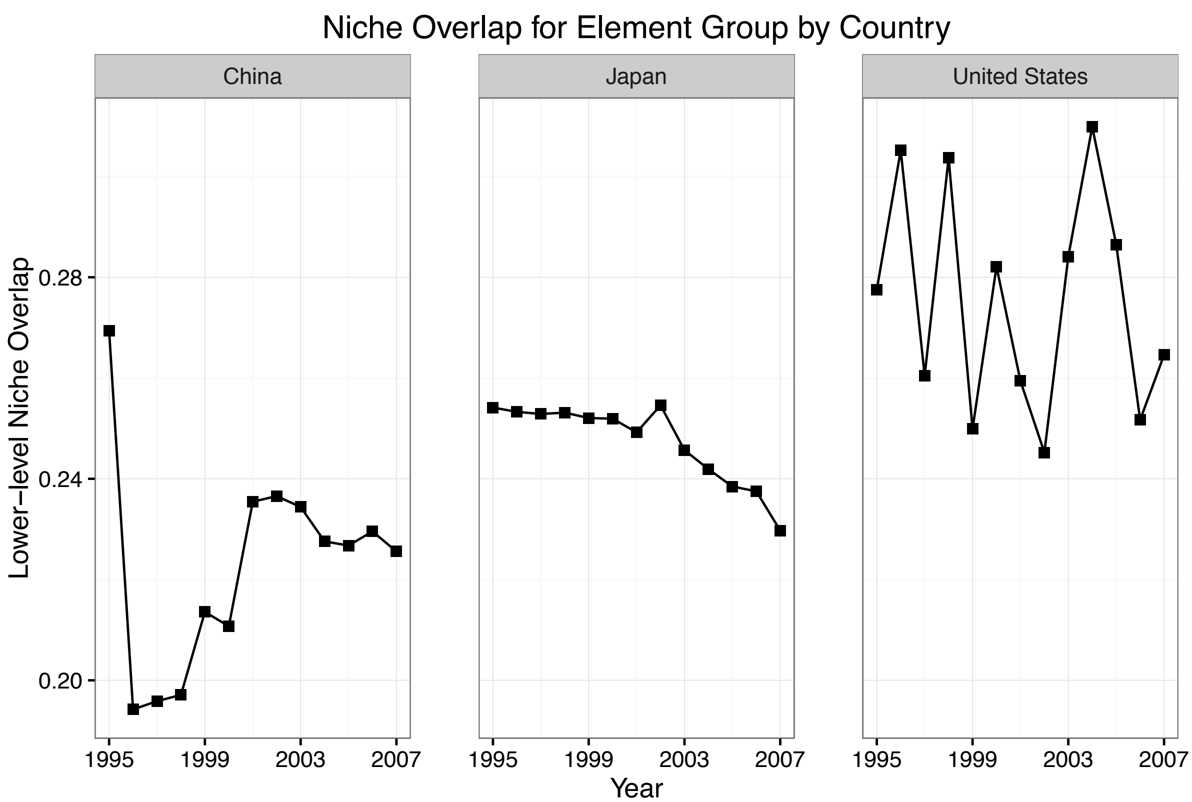


Figure 21. Niche overlap for the element group of the China, Japan, and U.S. rare earth network from 1995-2007

Niche overlap does a good job of highlighting networks that might be using substitution, which lead criticality practitioners to take a closer look at the details of the network. It also highlights networks that may not be taking full advantage of the potential of substitutability.

3.2.8. Vulnerability

Vulnerability is the importance of the elements to the product group (products per element). By 2007, China's elements were relying on a higher number of products than U.S. or Japan, Figure 22. This increased reliance on a multitude of products makes it more difficult for the network to handle losses of elements (more products affected in the event of supply disruption of an element). Similar to trends in other metric results, Japan's vulnerability was fairly constant and U.S. increased over time. A higher value would seem to be better for the system (more products per element), but because it reflects the importance of the elements to the products, higher values signify a greater demand for the elements. What is not clear is whether the elements are being utilized for a specific purpose (function) or if a country with higher vulnerability (China) is utilizing substitution in some of their applications, which seems possible given the increase in China's niche overlap.

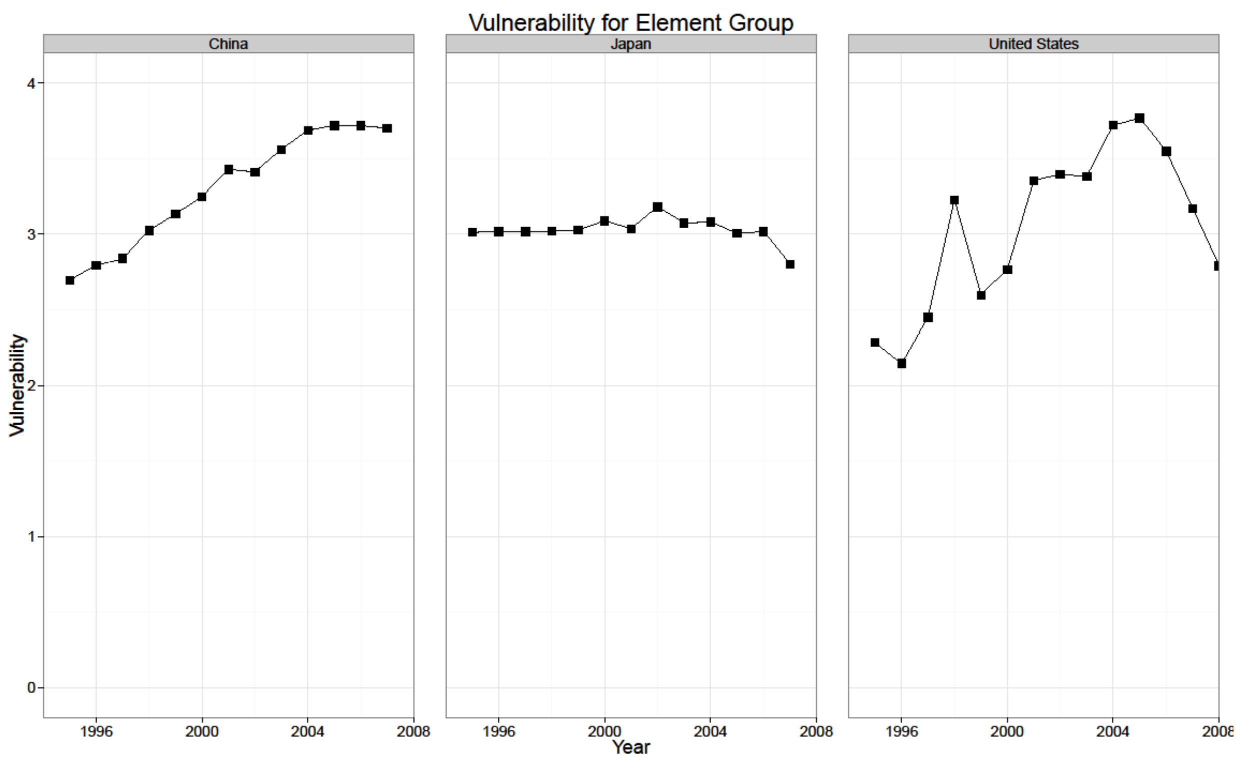


Figure 22. Vulnerability for the Element group in the REE networks of China, Japan, and the U.S. from 1995-2007

3.2.9. Extinction Slope

Extinction slope represents the robustness of the product-level to elemental "extinctions." This is key for criticality because it indicates how the product markets will fair if there is a supply disruption or scarcity of an element.

The U.S., for 2007, had the lowest tolerance to extinctions of elements, Figure 23. Given this, industries or technologies in the U.S. might have the most difficulty if a given element has a severe supply risk (i.e. via price spikes); however, its 2014 tolerance is on par with Japan's 2007 tolerance. Japan had the highest tolerance over the time considered, but only China had a change that was statistically significant (P < 5%).

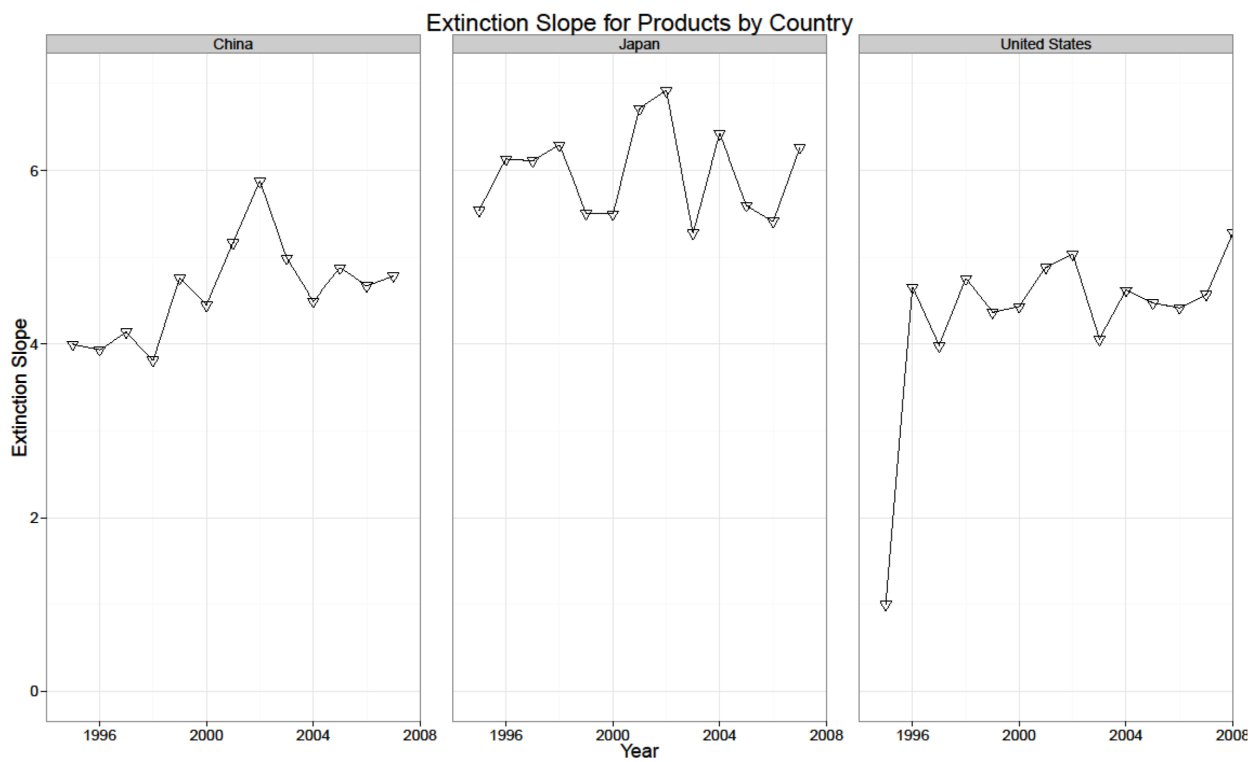


Figure 23. Extinction slope for the Product Group of REE networks from China, Japan and the U.S. for 1995-2007

In the more recent years, the U.S. has been using fewer elements in fewer products, which may account for its increasing robustness. This is likely due to the United States' lack of RE mine over that time period (U.S. Geological Survey 1996-2015).

Extinction slope is useful for understanding the resilience of a country's products to the removal of elements. In an ecological study, it was found that highly connected webs could delay secondary extinctions (Dunne, Williams, and Martinez 2002b). Secondary extinctions are extinctions caused by extinctions of other species in the ecological web. Comparing the extinction slopes to connectance values for the rare earth webs, the U.S. or Japan should have the highest extinction slopes based on its connectance, but the U.S. extinction slopes are no better than China. This is likely due to the increasing specialization in the U.S. as described by the specialization asymmetry. However, Japan does have both high connectance and the highest extinction slopes, which is hopeful evidence for this relationship.

3.2.10. Partner Diversity

Partner diversity measures the importance of an element to a higher number of products. Results show that the most important elements in 2007 were Ce, La, Pr, and Nd, Figure 24. For China, Ce and La partner diversity increased, indicating that they were becoming important for an increasing number of products. Conversely, Nd, Pr, and Y were decreasing in use over this same time in China. For Japan, most of its elements were consistent in their level of importance to products, but Ce and La were more important than the others for several products. For the U.S., several elements were increasing in importance over the time period studied, including Ce, Gd, La, Nd, Pr, and Y. It is possible this increase in the U.S. came with a surge of a variety of small electronics requiring various rare earths for a larger variety of applications (screens (LEDs and glass polishing), vibrational units (magnets), lasers, etc.). China and Japan's products were most reliant on Ce and La, while products in the U.S. were using La, Nd, Ce, and Pr.

Metrics such as partner diversity are best used in combination with criticality indicators or elements of interest because it reveals the potential impact of its criticality on products. For example, if Nd is designated as critical in the U.S., partner diversity studies reveal that it is increasing in importance for an increasing number of products, which amplifies its criticality.

Another interesting feature of partner diversity is considering changes over time, for some elements, it is possible to predict if an element is likely to be used by additional products. Partner diversity for China's Ce and La use show a clear upward trend; therefore, it is likely these elements will be used by an increasing number of products. Because these elements are growing in importance, their potential criticality would have increasing and far-reaching impacts on products.

Other elements in China's network show a decrease in partner diversity, notably Y, Nd, and Pr. For these elements, their importance for a higher number of products is decreasing, so the applications affected by their impending criticality would be fewer than that of Ce or La.

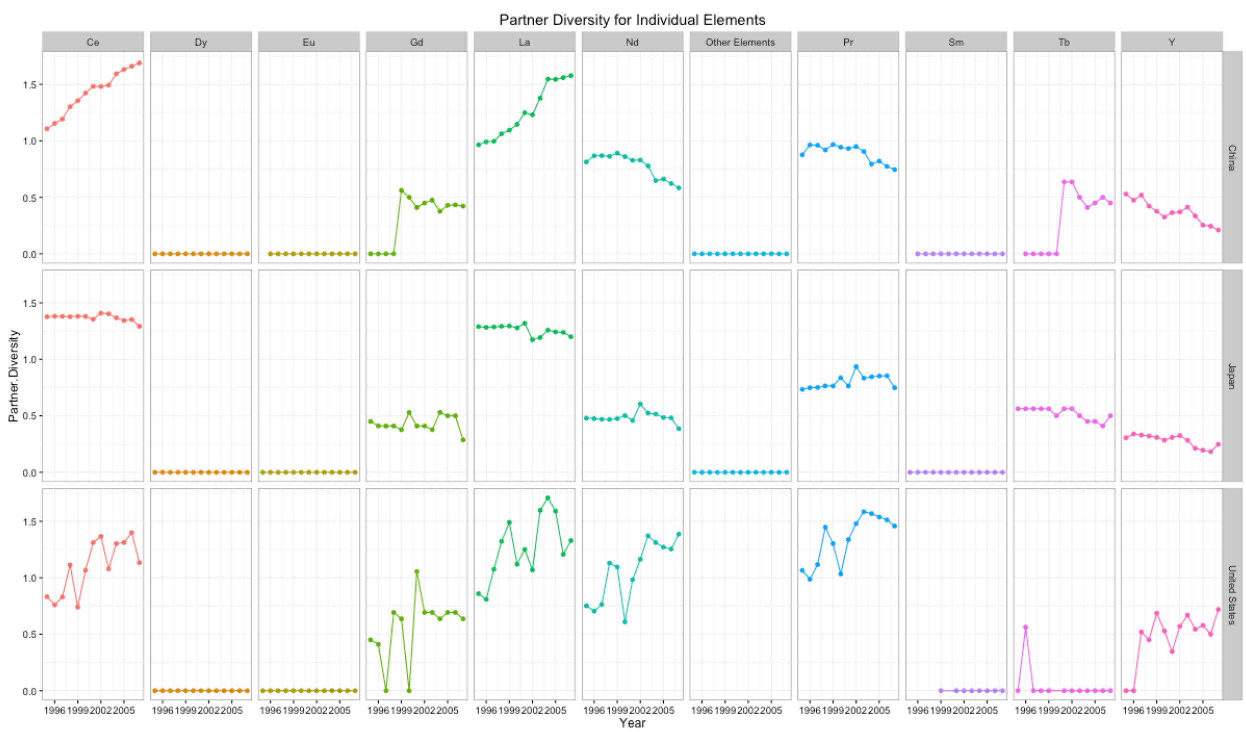


Figure 24. Partner diversity for each country and rare earth element from 1995-2007

Partner diversity has potential as a countermeasure for criticality as it highlights the number of products utilizing an element. A key mitigation strategy for material criticality is recycling development. For elements that are important to a wider variety of products, many sources would be available for recycling. Conversely, elements important to only one or two products have potential for providing a more concentrated waste stream for recycling. Understanding these features is important for an optimal waste stream for rare earth recycling. If products are plentiful, then a large waste stream will be available for recycling, and if the element concentration is high in particular products, then those products will be desirable as recycling processes could be minimal.

3.2.11. d'

d' is a measure of elemental specialization. It highlights elements that are used by one or few products. In China, several of the elements were increasing in specialization, but for the most part resulted in low values of specialization, except for Y, Figure 25. Yttrium for China and Japan showed to be the most special element (high d'), although Ce, La, and Nd appeared to be increasing in specialty for China, Ce and Nd for Japan. In the U.S., only Dy seemed to be increasing in specialty in its end uses, and most other elements were decreasing. These results are slightly contrary to some of the other measures which highlight the increasing diversity and flexibility of the Chinese and Japanese systems. Despite this, d' is useful for criticality at an elemental level, as it highlights vulnerable element-product pairs. China and Japan have a high d' for yttrium, so the product that yttrium is unique for could experience issues with a supply risk and/or price spike if substitutes are limited or non-existent.

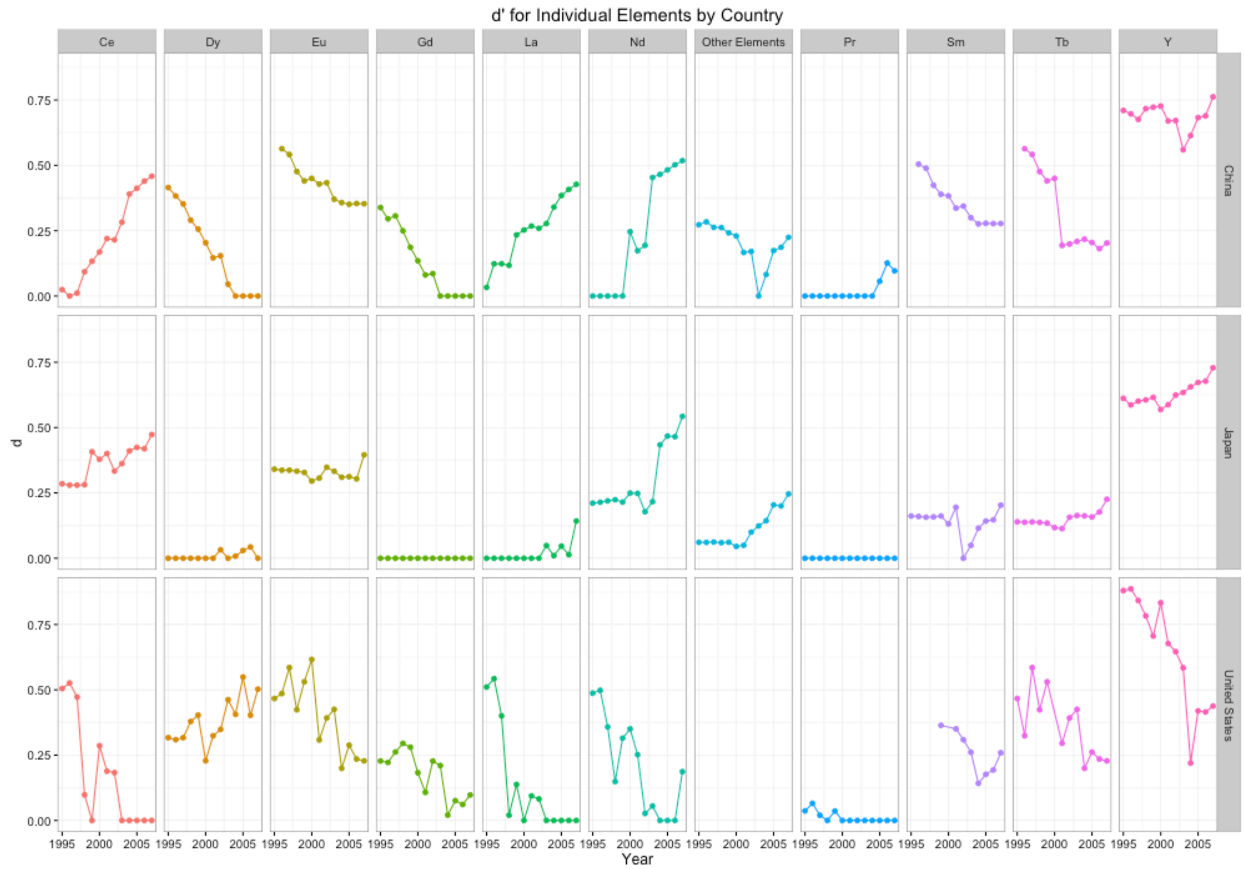


Figure 25. d' for individual rare earth elements for each country from 1995-2007

For most of the years and many countries, yttrium had the highest d' at about 0.75. d' also accounts for the rarity of the product, so Y is high because it is used by one or two products and these products also happen to be rare with respect to the entire system. Y is unique to the product using it, so the product will be more vulnerable to supply risks. If supply of Y is low, and the price spikes, the product requiring yttrium will likely see a price spike. For Japan in 2007, phosphors and glass additives were using yttrium. If yttrium supply were inhibited, then products containing phosphors and glass would likely see a price increase.

In the U.S., elements appear to be converging in terms of d'. This is a good thing because it means that the elements being used are not "special" to the products using them. Perhaps this is a result of these elements not being produced in the U.S. during the early 2000s, meaning, industries in the U.S. started to use more of a mixture of elements rather than relying on one or two (possibly compromising some level of performance), or the U.S. is reducing the number of products it produces (U.S. Geological Survey 1996-2015). An example would be substituting some of the Nd in permanent magnets for Pr and/or Dy, or other substitutes as proposed by the Department of Defense (U.S. Department of Defense 2013).

Highly specialized elements can end up with a low d' because they are used by one product, but cannot claim "specialization" because they are not unique to the product. In the U.S. for 2007, Sm was used only by "others," and used only by "magnets" in Japan for 2007, but both "others" and "magnets" utilized a variety of elements, so Sm is not considered "specialized" because it is not a unique element for those products.

3.2.12. Normalized Degree

Normalized degree measures degree, but is scaled based on a node's number of potential interactions. Degree is basically a measure of the element or product's involvement in the web. It is also used as a measure of specialization, indicating how many or few interactions an elements or product experiences. This metric was chosen for its prevalence in not only ecological literature, but all network types. As presented in Table 5, the average degree for the rare earth networks was about 3.9. Compared to other networks, this value is fairly high given its relatively small size. For the normalized degree, China had a few elements with relative high values Ce and La especially, Figure 26. Nd and Pr were also used by >50% of the products available for the years evaluated. The majority of the other elements used by China had low values. Trends for Japan's elemental normalized degree were very similar to China in both the highly connected elements and low connected elements. Although not as consistent as China and Japan in normalized degree values, the trends in the U.S. were also similar. These results make sense because Ce and La are typically used in the most products and in the largest quantities due to their availability being the highest of the rare earths (Gunn 2014).

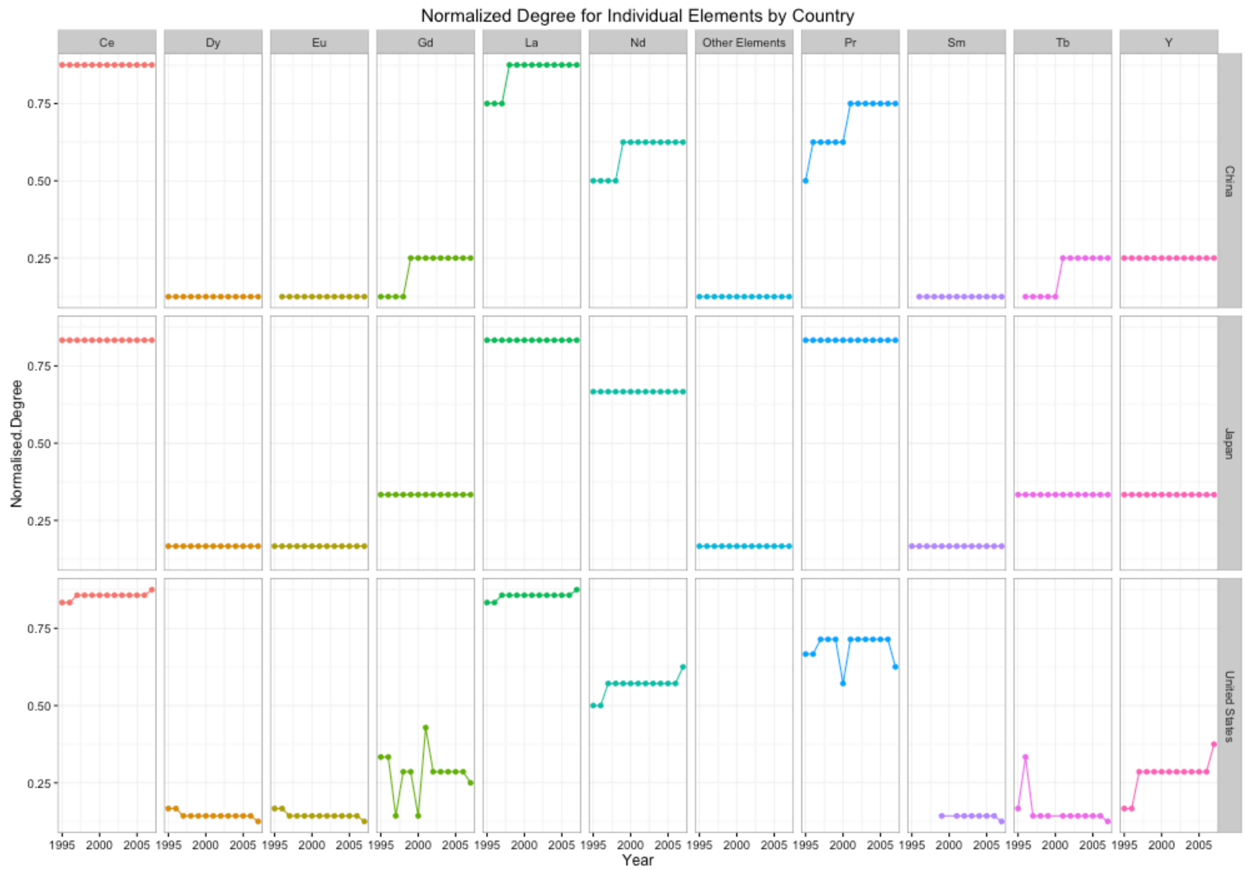


Figure 26. Normalized Degree for Individual Elements in China, Japan, and the U.S. from 1995-2007

Normalized degree for the products is interesting because across all countries, compared to the elements, it appears that the distinction is smaller between products utilizing several elements and those using fewer, Figure 27. In China, the highest use for elements was glass additives followed by phosphors. Glass additives and phosphors especially make use of a wide variety of elements. Depending on the purpose of the glass, addition of rare earths can change the properties significantly by making it more impact resistance, shock resistant, or even less likely to absorb certain wavelengths of light. Phosphors also utilize various rare earths to produce the red, green, and blue colors displayed on computer, phone, and television screens. In Japan, these were also the products with the highest elemental utilization. However, in the U.S., glass additives were not prevalent, and instead "other uses" dominated along with phosphors. This may only be a feature of the data, and difficulty in consistency across country reporting, but Ceramics were only included in 2007 for the U.S., but were utilizing about 50% of the REEs. Furthermore, battery alloys and glass additives were not used in the U.S. at all and "other uses" were not reported for China and

Japan. Normalized degree gives a more in-depth look at what is occurring at the product-element pair level that network- and group-level cluster coefficient cannot convey. These figures together, Figure 26 and Figure 27, give a complete picture of the relationships of the individuals within the REE network for each country, while capturing changes over time.

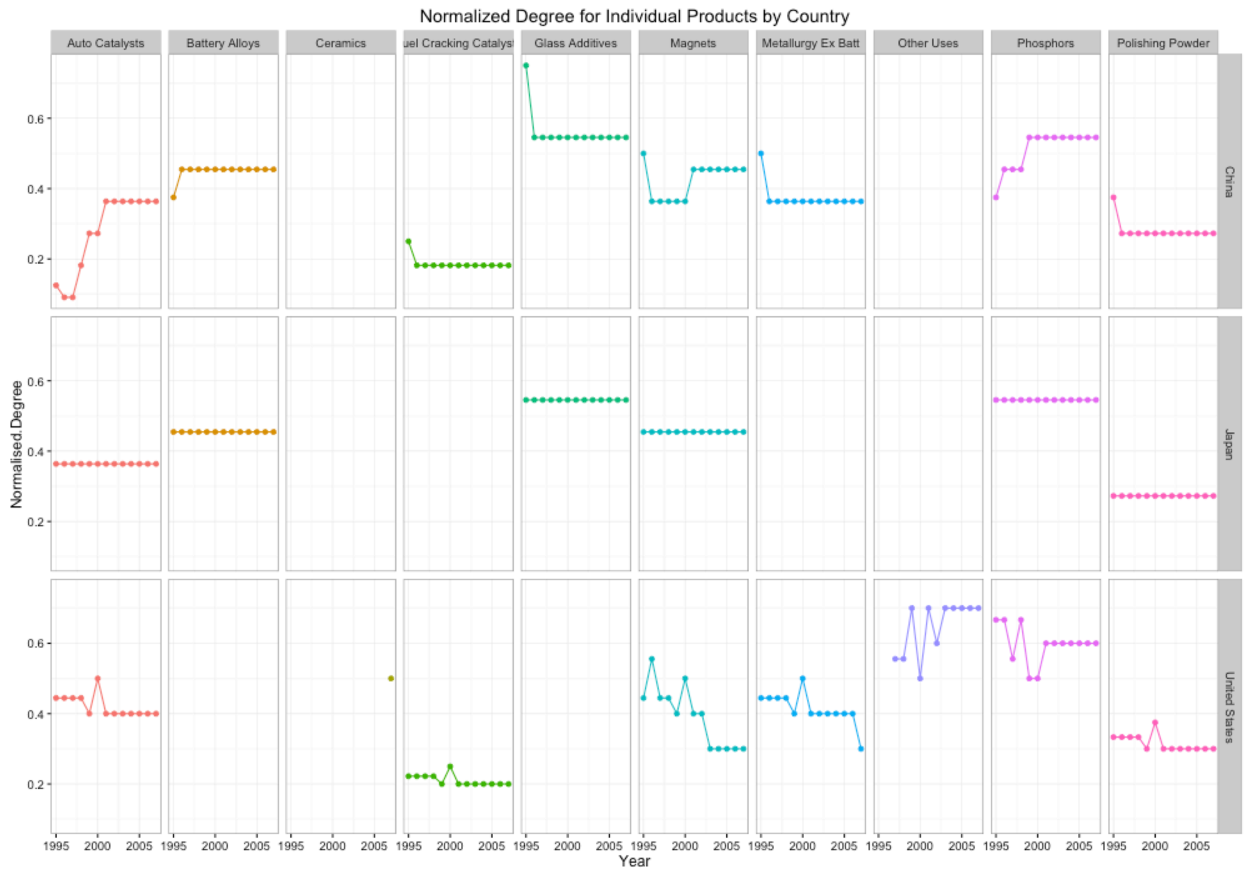


Figure 27. Normalized degree for Products utilizing rare earths in China, Japan, and the U.S. from 1995-2007

3.2.13. Weighted Betweenness

Weighted betweenness is the qualitative measure for betweenness. Betweenness is a network centrality measure that quantifies a node's influence over the network. It highlights how an individual in the network might be able to influence the flow of materials. At first glance, this does not seem like it would be useful for criticality because the materials are not necessarily "traveling" between the nodes. However, some elements may seem to have more control over how their use is distributed amongst the products. For the individual elements, in China, Ce and

Nd have the most influence, while many others have none or very little, Figure 28. The same is true for both Japan and the U.S. La and Y have some influence, but it is very little. Ce and Nd likely have the most influence because they are both highly connected and used in the large quantities. Compared to China and Japan, Nd in the U.S. has a declining weighted betweenness, signaling that it is losing its influence in the system. Overall, Ce and Nd have the highest betweenness, so changes in the amounts of these elements would likely have influence over a large portion of the system. Given a supply risk of one of these elements, it is possible that the impacts will affect many of the elements and products.

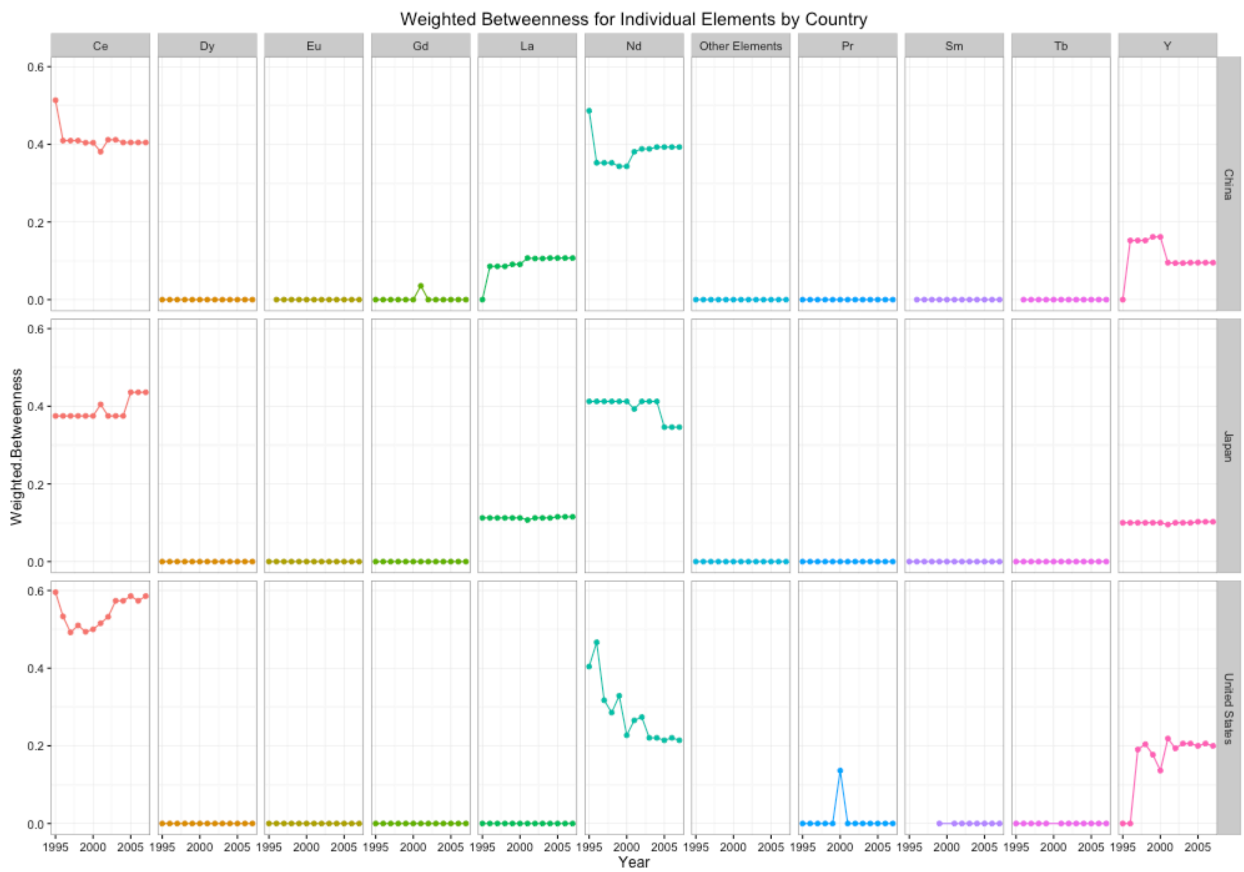


Figure 28. Weighted Betweenness for Elements in China, Japan, and the U.S. REE networks from 1995-2007

For the products, weighted betweenness yields very different results across the countries, Figure 29. China's most influential products are glass additives and metallurgy applications (except batteries), where metallurgy is fairly high >0.50. Japan's most influential products are battery alloys and glass additives, and the U.S. had only one product >0.50 over the years, which was auto catalysts (followed by "other uses"). What the product weighted betweenness indicates is how much the product market can potentially influence the elements it uses, including increasing or decreasing element demand. Criticality studies are concerned with future growth of product sectors related to materials they are interested. Knowing which sectors you expect to change and which elements are used in those products, you could use weighted betweenness to know how much influence that product will have over the element(s) of interest.

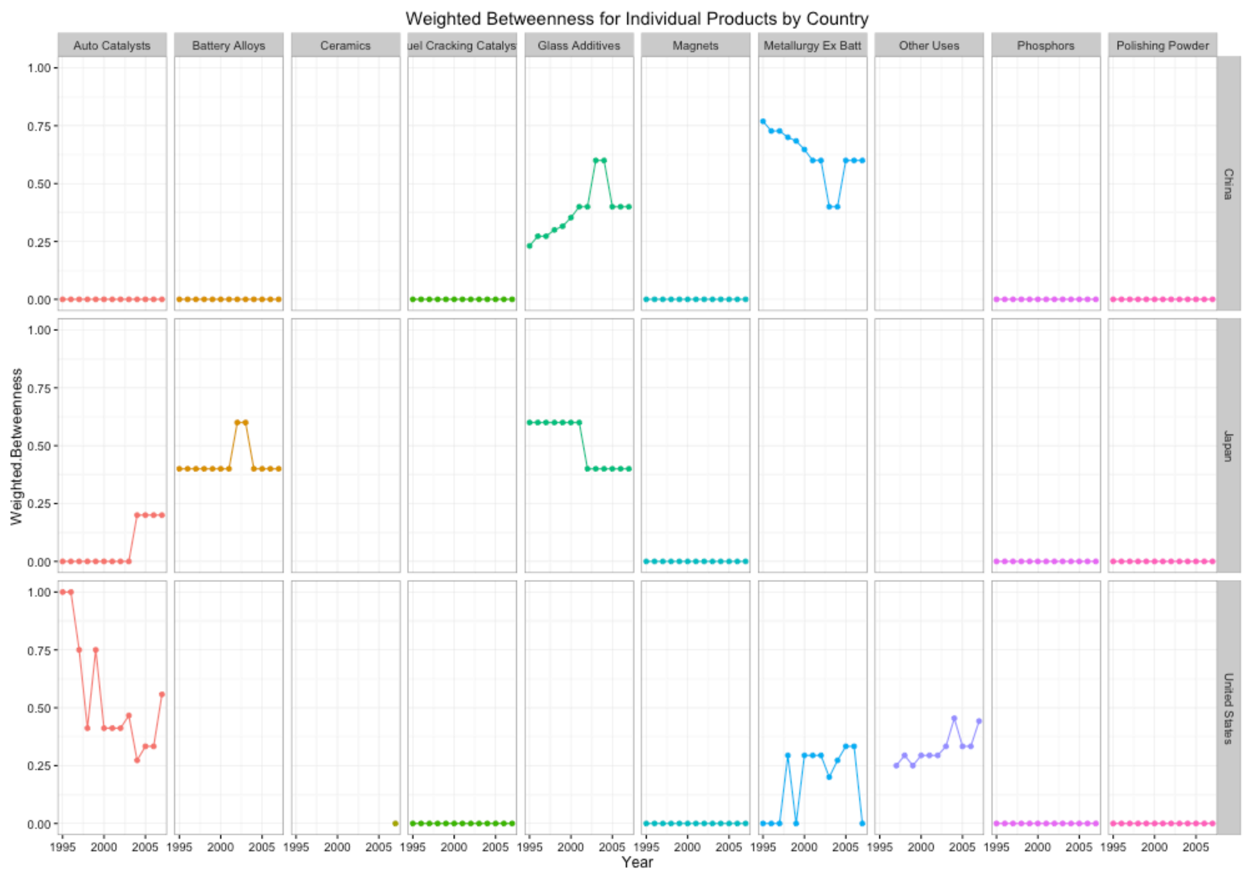


Figure 29. Weighted Betweenness for Products in China, Japan, and the U.S. REE networks from 1995-2007

3.2.14. Interaction Push-Pull

Interaction push-pull is indicative of whether an element or product is influencing others or if it is being influenced. At the elemental level, this means the element is either "pushing" the products (values of 1) or the element is being "pulled" by the products (values of -1). In China, only Ce and La had positive values indicating that they influenced products, while all other elements, except Nd, were being pulled by the products. Nd had values of interaction push-pull near zero, along with Pr, which indicates that it is neither influencing or being influenced. In Japan, most of the elements were neutral or negative, except Ce, indicating that they were being influenced more so by the products. Ce was barely positive for Japan, which means that it has more influence on the products than the other elements. The U.S. had trends similar to China, but slightly more or less depending on the element. What is interesting here is rather than elements dictating the products, the products have most of the influence in the REE networks, with a few exceptions. It is possible that if supply of rare earths were included in this study, forming a tripartite, the supply of rare earths would have the most influence.

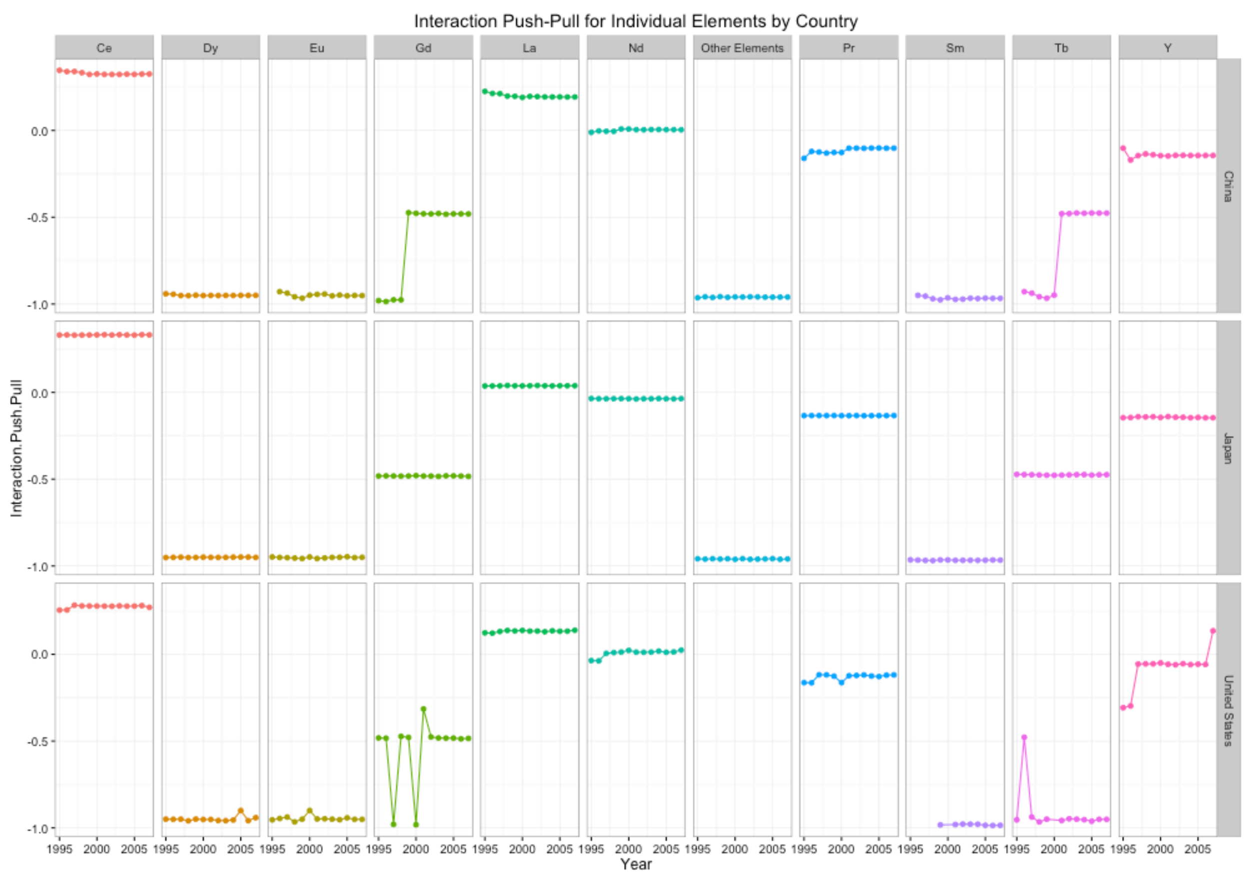


Figure 30. Interaction Push-Pull for Elements in the REE use network for China, Japan, and the U.S. from 1995-2007

Positive values indicate the element is influencing the products, more than the products influence the elements, while negative values indicate the element is being "pulled" or influenced more so by the products.

3.3. Conclusions

Analyses of the results helped in narrowing the focus on metrics that capture the most the most variability in the data. These selected metrics highlight interesting features that prove network and ecological network analysis as useful tools for analyzing critical material systems. These concepts are summarized in Table 7, but should not be taken as comprehensive. There is still much more to learn about the material system and its potential implications for criticality.

Table 7. Summary of network metrics and concepts useful for critical material systems

Metric	*Criticality Concepts*	*Reason to Use*
Cluster Coefficient	Network structure, elemental or product importance	• To study the structure of connections
Shannon Diversity	System robustness	• Identify how much change the system can endure (i.e. how much supply disruption to occur before network is fragile)
Interaction Evenness	Reliance on single element-product pair	• Identifies pairs that are dominating the network
Connectance	Complexity or connectedness of the system	• Benchmark with previous studies • Can be indicator for other system properties (effects need to be studied first)
Specialization Asymmetry	System-level vulnerability	• Highly specialized systems are more sensitive to slight changes
Niche Overlap	Substitutability	• Sign that the country is taking advantage of substitutes • More useful when comparing elements beyond RE • Measures built-in redundancy of element uses
Vulnerability	System-level importance of elements to products	• Compare across countries which systems are more reliant on elements
Extinction Slope	System tolerance to elemental removal	• Highlights how the system will react to losses of elements • Could be modeled to see which criticality mitigation strategies improve extinction slopes
d'	Element specialization level	• If element is specialized to a product, it may be for an important function • If an element is not specialized, and becomes critical, it will have a broader impact on the products using it
Partner Diversity	Increasing elemental importance	• Is the element becoming more important? • Is it likely to be utilized by additional products in the future (i.e. as products are developed, is it likely to be used in those products)
Normalized Degree	Element or product importance	• Element and product level view of cluster coefficient • Determine which elements or products are key components
Weighted Betweenness	Influence of element or product	• Identify elements or products that are in positions of control • Which elements are likely to have more control over use in products, given changes in the availability of the element
Interaction Push-Pull	Are elements or products the most influential?	• At the element and product level, determines which has more influence over the other • Is demand from products dictating element use or is availability of elements dictating use in products

3.3.1. Summary of Network Results

Visually inspecting network graphs highlights areas for potential criticality, but the graphs not consider magnitude and therefore make it difficult to assess the underlying structure. Results for the measures that qualitatively and quantitatively measure features of the visual network are summarized here.

Cluster Coefficient was mainly used in this analysis for its continued use in network studies. Although the rare earth networks were very small compared to historical analyses, the cluster coefficients fit in with the average. Cluster coefficient has been used as a robustness indicator in previous works, but further analysis is needed to understand if this is true of material systems.

Shannon Diversity was also selected for its prevalence among ecological studies and other disciplines. It appears that Shannon diversity followed trends in the GDP of the countries analyzed, and diversity has been hailed as a stability indicator; however, these concepts need to be studied further to make definitive conclusions.

Interaction Evenness goes along with diversity and is an important concept to ecologists. At the network-level, evenness does point out if the system is potentially reliant on a single element-product pair, which is a vulnerable situation depending on the likelihood of supply disruption for the element or significant demand for the product resulting in a supply gap of the element.

Like Shannon Diversity and Interaction Evenness, Connectance was also selected for its wide-spread use amongst networks, ecology, and even industrial ecology. For connectance, the rare earth webs were comparable to other major studies. China had the lowest connectance, which indicates it could be most vulnerable to removal of elements, but further analysis on species removal is necessary to determine anything conclusive.

Specialization asymmetry shows increased specialization in the U.S. rare earth web that reflects a more vulnerable network than that of Japan or China. Vulnerability showed China to have an increased reliance on the elements, but it is not clear whether China is utilizing more elements in more products due to growth or if it is guarding against criticality via element substitution.

Despite its high connectance, the U.S. had a low tolerance for extinctions. This is counter to some of the results by ecological analysis and warrants further study to better understand how the measures are related for a material web. A possible explanation for this disconnect is substitution. If substitution is being utilized, a system will be more diverse with a decreasing specialization asymmetry, but a higher extinction slope and vulnerability.

Niche Overlap, with advanced resolution and research, could highlight areas for studying substitution. High values also indicate redundancy within the network, which is commonly associated with resiliency.

As indicated by partner diversity, elements in China's network, namely Ce and La, are likely to be utilized by an increasing number of products, while some elements, Nd, Pr, and Y are being utilized by fewer and fewer products. Japan's system had very little variation and the U.S. had too much variation to discern anything conclusive regarding partner diversity. Because partner diversity is related to the number of products utilizing an element, we can understand some implications for criticality mitigation with respect to recycling. Elements utilized by a wide variety of products will likely provide a complex, but large waste stream for obtaining secondary rare earths. Conversely, elements used by few products could provide a more concentrated waste stream for rare earth recovery. Both of which are important for understanding a secondary supply of rare earths.

Normalized degree was helpful at seeing the "species-level" connectance. Important for understanding the components of the rare earth system, it highlighted where products were not being used at all, and also which products were more important to each country and also the most important elements to those countries based on amount used and number of products.

Weighted betweenness, although not fully demonstrated as a criticality concept, measures the influence that elements or products have in the network. Similarly, Interaction push-pull highlights whether elements are influencing products or if the products are influencing the element. These "influence" components of the system are important to understanding how the system is likely to respond to external changes. For example, if demand for a product increases and supply is restructured for an element at the same time, which is more likely to affect the system and other individuals?

Ecological network analysis can provide new insights for critical materials and their systems through a comprehensive analysis of the material network structure and relationships amongst the various measures. Although studies in ecological networks do not always translate to material networks, as illustrated by Figure 20, they provide a rich resource for potential relationships and hypotheses for advancing critical materials research towards a sustainability system-stability approach.

3.3.2. Limitations

While this analysis highlights the usefulness of analyzing a material system and the potential for a deeper understanding of criticality, especially incorporating temporal systems-analysis of the demand-side. Still, there are several limitations that persisted for this analysis.

A major limitation of this work is the size of the bipartite network. Bipartite webs, especially in the case of these particular rare earth webs, are too small to determine degree distribution (small world, power law, etc.), which provides tremendous insight for networks (Barabasi 2002, Dunne, Williams, and Martinez 2002b).

This analysis is limited to countries and years available, so outcomes may not be relevant to the current material system. The most recent data used in this analysis is not new or recent, and for criticality studies, having the most recent data available is important for mitigation strategies, especially for cases where a supply disruption could occur in the short-term.

It is also unclear how the quality of the underlying data affects the outcome of the metrics analyzed. While this type of analysis is not as data intensive as other criticality studies, as demonstrated by ecology, the quality of the data is very important. For the rare earth case-study, the underlying material flow analysis data relies on single source for assumptions for elemental distribution amongst products. The data seems to be a good representation of each country for those years, but it is uncertain how the underlying assumptions propagate in the metric analysis. While this is a limitation of this analysis, it is a persistent problem in all researchers of the rare earth elements (U.S. Department of Defense 2015).

Material system topology is fundamentally different from ecological or small world networks, and without further study of material networks, it is difficult to make general conclusions about critical material networks. An expansion of the data set could allow for calculation of metrics that need more data points (e.g. degree distribution) and are well-known indicators of underlying network structure and a staple in network or ecological network analyses. However, it is likely that most material bipartite networks will be small in size compared to even food web networks, which are considered small in comparison to real-world networks (Dunne, Williams, and Martinez 2002a).

Methodologies that strengthen the findings of ecological network analysis are unavailable for this work. Typical bipartite network analysis utilizes null models to compare and contrast ecological systems for various metrics, but this could not be replicated due to limited data points and lack of consideration for other material systems. This type of statistical analysis and comparison to null models would significantly strengthen the findings of this work.

3.3.3. Recommendations

Future work would do well to expand the rare earth bipartite web to a more integrated food web, as well as, explore other critical material systems for similar patterns. Expansion of the web and comparison to other webs or null models would allow for understanding the relationships between web size, connectance, robustness, and resilience of these systems so that the outcomes would be more conclusive and the network structure of material systems can be established.

Applying these concepts to other potentially critical material systems, such as the platinum group metals, may be a great way to corroborate this work and take advantage of the potential this type of analysis holds.

There is also room to conduct more analysis on compounding metrics. Metrics such as partner diversity are best used in combination with criticality indicators or elements of interest because it reveals the potential impact of its criticality on products. For example, if Nd is designated as critical in the U.S., partner diversity studies here reveal that it is increasing in importance for an increasing number of products, therefore its criticality would be amplified. This highlights the need for practical applications for this analysis, for example, predicting recycling patterns (collect several products or few based on partner diversity or a similar measure). Understanding these relationships and expanding this analysis to include practical applicability would greatly improve this field.

Most importantly, to ensure the sustainability of our material systems, it is crucial that researchers keep working to understand the intricacies of these systems and work to understand how growth of clean energy technologies will impact other product markets and vice-versa.

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APPENDIX A. Material Webs and Sample Data

A-1. Full-Size Material Webs for 1995 and 2007

Following figures constructed using data from Du and Graedel (Du and Graedel 2013).

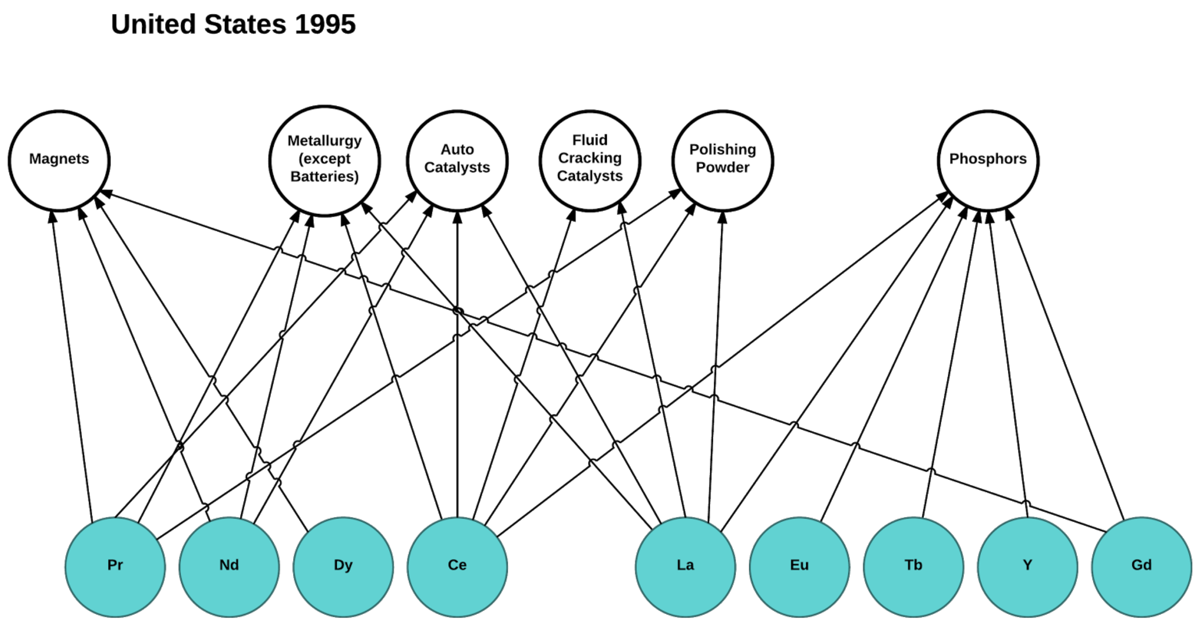

Figure 31. U.S. Rare Earths 1995 Bipartite Network

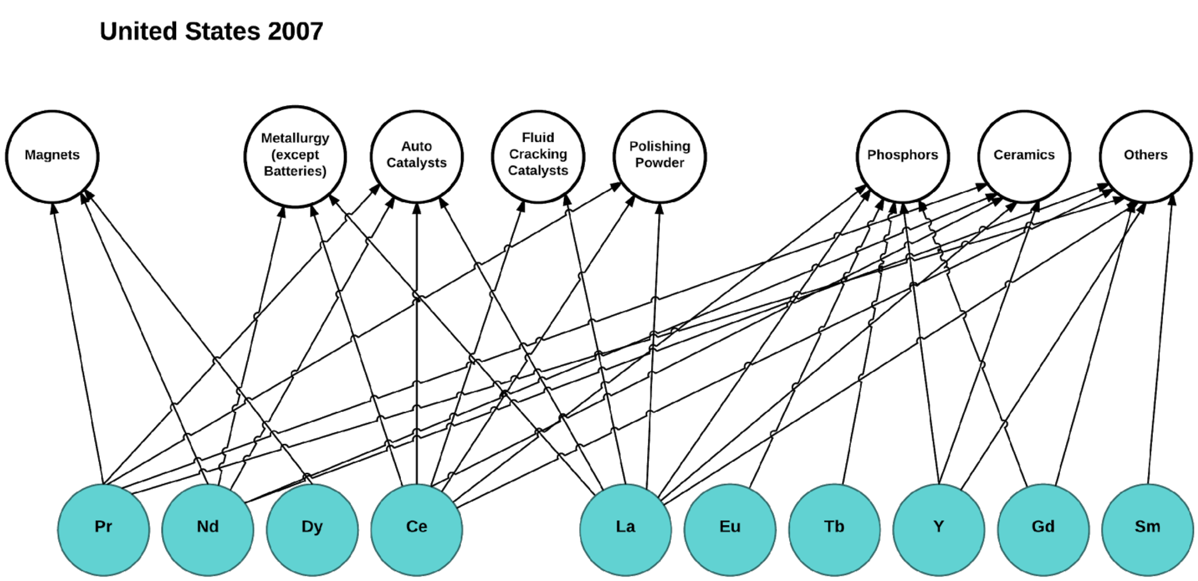

Figure 32. U.S. Rare Earths 2007 Bipartite Network

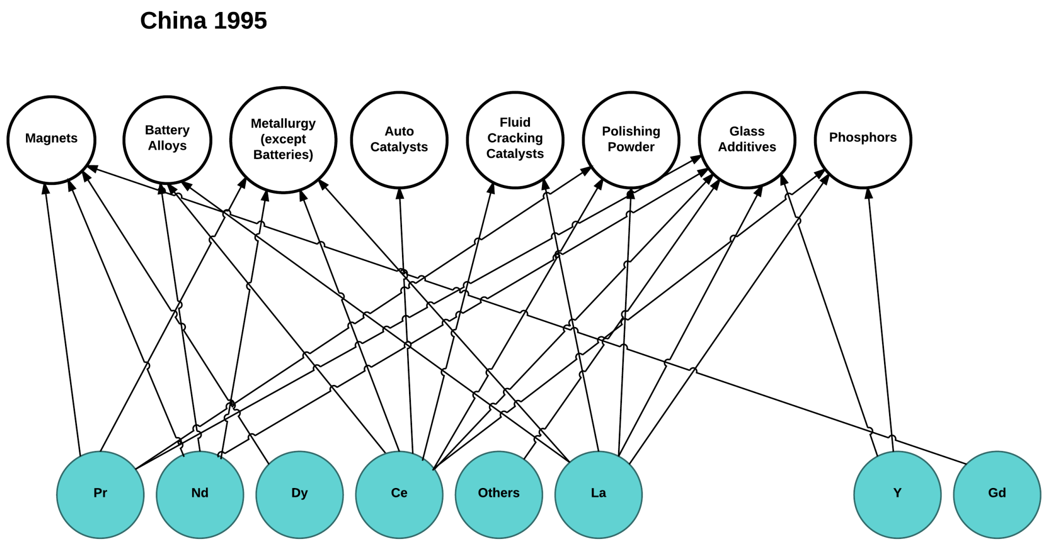

Figure 33. China Rare Earths 1995 Bipartite Network

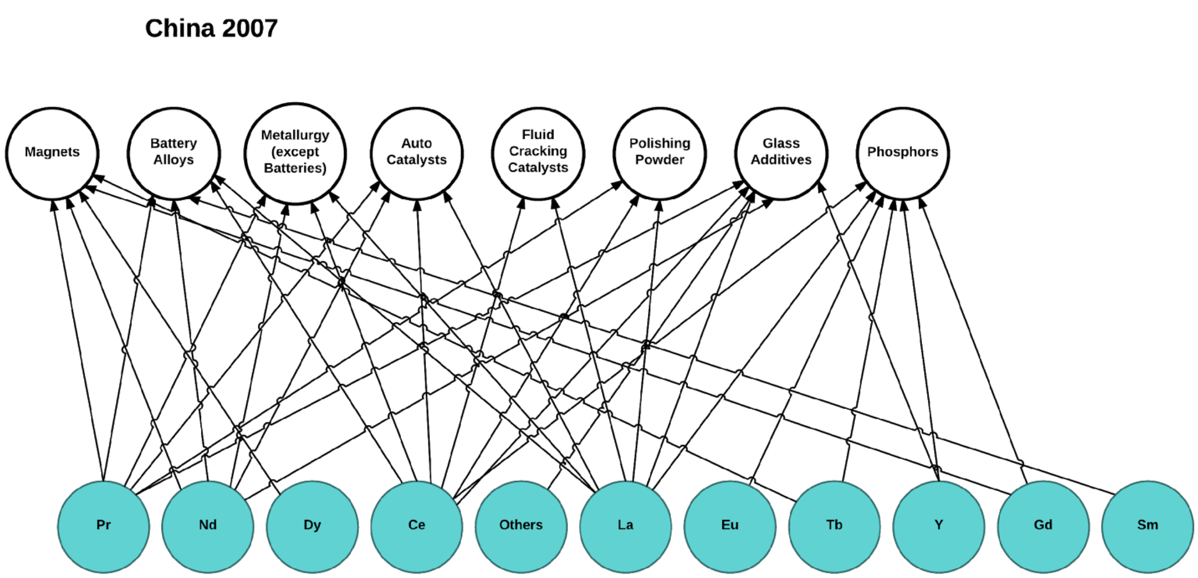

Figure 34. China Rare Earths 2007 Bipartite Network

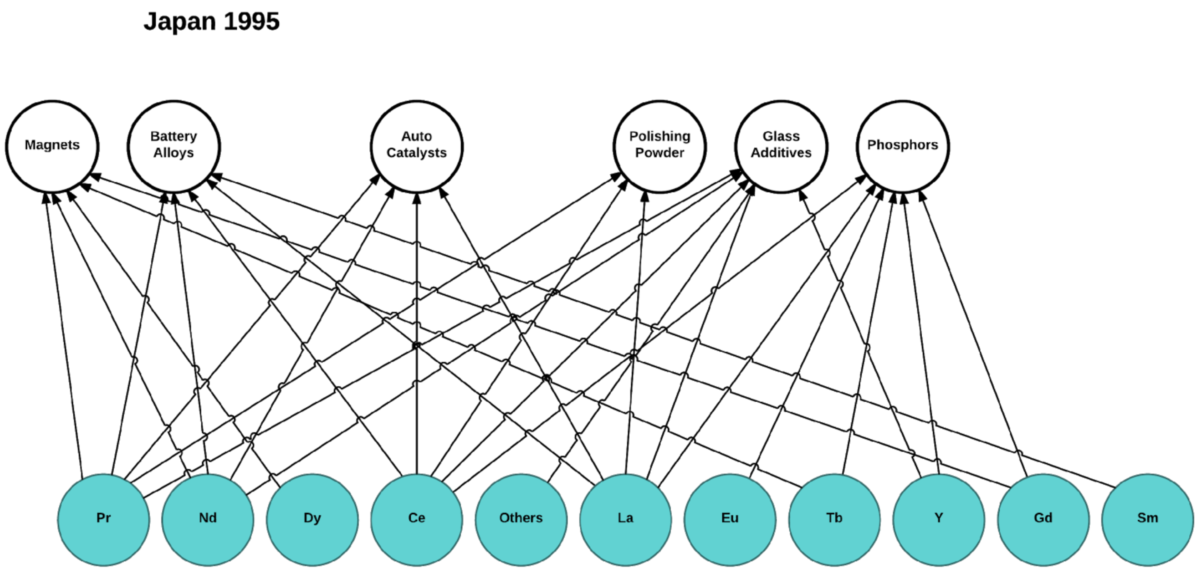

Figure 35. Japan Rare Earths 1995 Bipartite Network

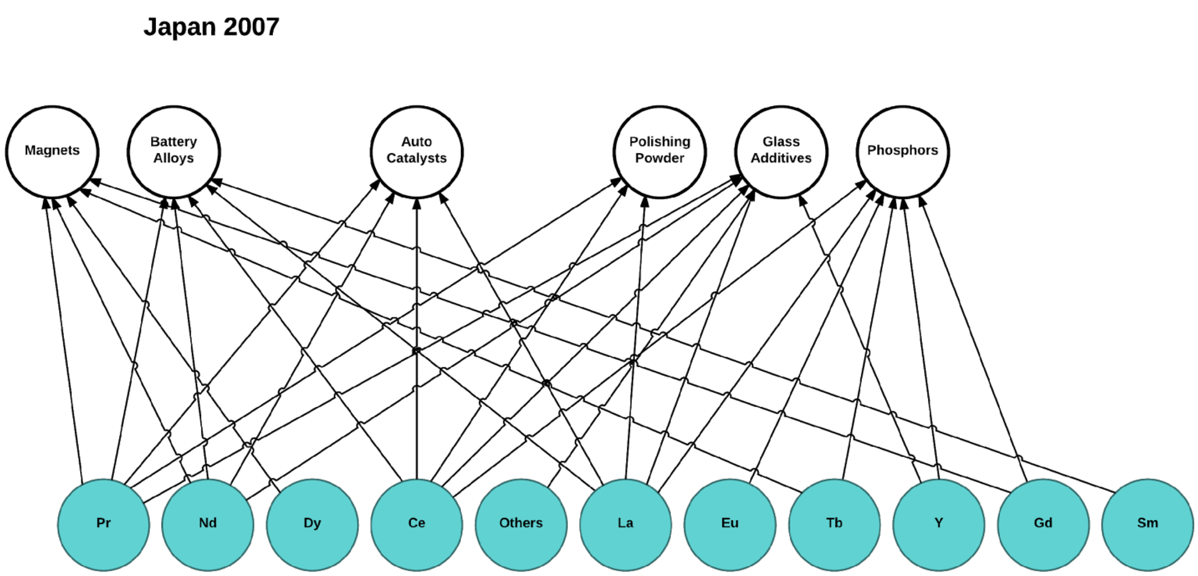

Figure 36. Japan Rare Earths 2007 Bipartite Network

A-2. Sample Data

	Rare Earth Elements			End Uses 2007 (Gg)										
	Atomic #	**Name**	**Symbol**	**Magnets**	**Battery Alloys**	**Metallurgy ex.batt**	**Auto Catalysts**	**FCC**	**Polishing Powder**	**Glass Additives**	**Phosphors**	**Ceramics**	**Others**	**Total**
CHINA	39	Yttrium	Y	0.00	0.00	0.00	0.00	0.00	0.00	0.13	2.28	0.00	0.00	2.41
	57	Lanthanum	La	0.00	2.30	2.45	0.10	5.81	1.76	1.62	0.28	0.00	0.00	14.32
	58	Cerium	Ce	0.00	1.54	4.89	1.84	0.65	3.64	4.45	0.36	0.00	0.00	17.37
	59	Praseodymium	Pr	4.00	0.15	0.52	0.04	0.00	0.20	0.07	0.00	0.00	0.00	4.98
	60	Neodymium	Nd	11.88	0.46	1.55	0.06	0.00	0.00	0.20	0.00	0.00	0.00	14.15
	62	Samarium	Sm	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15
	63	Europium	Eu	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.16
	64	Gadolinium	Gd	0.34	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.40
	65	Terbium	Tb	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.18
	66	Dysprosium	Dy	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.86
	Others			0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.00	0.27
	Source: Du and Graedel, 2013		**Total:**	17.11	4.60	9.41	2.04	6.46	5.60	6.74	3.29	0.00	0.00	55.25

Figure 37. Sample Bipartite Matrix

APPENDIX B. Bipartite Metric Results

Full results in this appendix were generated using the R codes in Appendix D and were compiled in Microsoft Excel using tidy data principles (Wickham 2014). Tidy data files were used to generate the results figures. Full result figures and associated codes are shown in Appendix C.

B-1. Network-Level

Table 8. Network-level Bipartite Metric Results

Network Bipartite Results 1 / 5

Country	Year	Connectance	Web Asymmetry	Links Per Species	Number of Compartments
United States	1995	0.43	-0.20	1.53	1
United States	1996	0.44	-0.20	1.60	1
United States	1997	0.43	-0.13	1.69	1
United States	1998	0.44	-0.13	1.75	1
United States	1999	0.41	-0.18	1.71	1
United States	2000	0.45	-0.07	1.67	1
United States	2001	0.43	-0.18	1.76	1
United States	2002	0.41	-0.18	1.71	1
United States	2003	0.41	-0.18	1.71	1
United States	2004	0.41	-0.18	1.71	1
United States	2005	0.41	-0.18	1.71	1
United States	2006	0.41	-0.18	1.71	1
United States	2007	0.41	-0.11	1.83	1
China	1995	0.41	0.00	1.63	1
China	1996	0.34	-0.16	1.58	1
China	1997	0.34	-0.16	1.58	1
China	1998	0.35	-0.16	1.63	1
China	1999	0.38	-0.16	1.74	1
China	2000	0.38	-0.16	1.74	1
China	2001	0.40	-0.16	1.84	1
China	2002	0.40	-0.16	1.84	1
China	2003	0.40	-0.16	1.84	1
China	2004	0.40	-0.16	1.84	1
China	2005	0.40	-0.16	1.84	1
China	2006	0.40	-0.16	1.84	1
China	2007	0.40	-0.16	1.84	1
Japan	1995	0.44	-0.29	1.71	1
Japan	1996	0.44	-0.29	1.71	1
Japan	1997	0.44	-0.29	1.71	1
Japan	1998	0.44	-0.29	1.71	1
Japan	1999	0.44	-0.29	1.71	1
Japan	2000	0.44	-0.29	1.71	1
Japan	2001	0.44	-0.29	1.71	1
Japan	2002	0.44	-0.29	1.71	1
Japan	2003	0.44	-0.29	1.71	1
Japan	2004	0.44	-0.29	1.71	1
Japan	2005	0.44	-0.29	1.71	1
Japan	2006	0.44	-0.29	1.71	1
Japan	2007	0.44	-0.29	1.71	1

Network-level Bipartite Results

Country	Year	Compartment Density	Cluster Coefficient	Nestedness	Weighted Nestedness
United States	1995	NA	0.44	27.55	0.23
United States	1996	NA	0.44	27.06	0.34
United States	1997	NA	0.44	28.35	0.15
United States	1998	NA	0.44	26.23	0.32
United States	1999	NA	0.40	20.62	0.26
United States	2000	NA	0.50	30.10	0.10
United States	2001	NA	0.40	24.55	0.34
United States	2002	NA	0.40	24.04	0.36
United States	2003	NA	0.40	23.38	0.37
United States	2004	NA	0.40	23.38	0.41
United States	2005	NA	0.40	23.38	0.39
United States	2006	NA	0.40	25.10	0.36
United States	2007	NA	0.35	22.44	0.34
China	1995	NA	0.38	13.91	0.51
China	1996	NA	0.36	19.46	0.39
China	1997	NA	0.36	19.46	0.39
China	1998	NA	0.36	24.57	0.37
China	1999	NA	0.36	24.19	0.43
China	2000	NA	0.36	23.80	0.42
China	2001	NA	0.41	26.36	0.39
China	2002	NA	0.41	25.41	0.38
China	2003	NA	0.41	25.88	0.42
China	2004	NA	0.41	25.34	0.43
China	2005	NA	0.41	26.36	0.41
China	2006	NA	0.41	25.82	0.42
China	2007	NA	0.41	25.25	0.42
Japan	1995	NA	0.45	31.44	0.15
Japan	1996	NA	0.45	32.06	0.18
Japan	1997	NA	0.45	32.06	0.17
Japan	1998	NA	0.45	31.44	0.21
Japan	1999	NA	0.45	31.66	0.17
Japan	2000	NA	0.45	30.99	0.18
Japan	2001	NA	0.45	30.99	0.17
Japan	2002	NA	0.45	30.99	0.21
Japan	2003	NA	0.45	31.83	0.18
Japan	2004	NA	0.45	31.44	0.16
Japan	2005	NA	0.45	31.44	0.16
Japan	2006	NA	0.45	31.44	0.15
Japan	2007	NA	0.45	30.99	0.14

Country	Year	Weighted NODF	Interaction Strength Asymmetry	Specialisation Asymmetry
United States	1995	26.80	-1.45	-0.09
United States	1996	29.80	1.55	-0.06
United States	1997	24.74	-1.17	-0.13
United States	1998	28.89	3.27	0.06
United States	1999	34.85	-0.72	0.30
United States	2000	21.60	1.35	-0.03
United States	2001	32.60	-4.30	-0.11
United States	2002	31.84	-0.26	0.05
United States	2003	35.63	0.44	0.25
United States	2004	39.29	24.50	0.45
United States	2005	39.29	0.80	0.27
United States	2006	37.53	1.55	0.47
United States	2007	39.47	1.12	0.24
China	1995	38.69	4.24	0.59
China	1996	32.05	0.03	0.38
China	1997	32.05	0.45	0.37
China	1998	33.65	-0.48	0.29
China	1999	32.49	-0.14	0.09
China	2000	32.61	-0.08	0.03
China	2001	31.57	0.92	0.03
China	2002	31.57	-1.82	0.03
China	2003	33.25	0.51	-0.02
China	2004	33.37	0.53	-0.04
China	2005	32.53	-0.54	-0.06
China	2006	32.53	-0.38	-0.05
China	2007	32.13	-0.32	-0.04
Japan	1995	29.14	-1.34	0.13
Japan	1996	29.14	-1.29	0.13
Japan	1997	29.14	-1.38	0.13
Japan	1998	29.14	-1.68	0.15
Japan	1999	29.14	-2.92	0.03
Japan	2000	28.19	11.95	0.03
Japan	2001	29.14	-1.31	-0.03
Japan	2002	28.31	-13.89	0.04
Japan	2003	28.67	1.43	0.06
Japan	2004	27.95	0.55	-0.08
Japan	2005	27.48	-1.39	-0.07
Japan	2006	27.48	-1.04	-0.05
Japan	2007	27.48	0.47	-0.01

Network-level Bipartite Results

Country	Year	Linkage Density	Weighted Connectance	Fisher Alpha	Shannon Diversity
United States	1995	2.05	0.14	NA	2.03
United States	1996	1.96	0.13	NA	1.98
United States	1997	2.14	0.13	NA	2.03
United States	1998	2.65	0.17	NA	2.25
United States	1999	2.28	0.13	NA	1.96
United States	2000	2.40	0.16	NA	2.24
United States	2001	2.81	0.17	NA	2.53
United States	2002	2.76	0.16	NA	2.42
United States	2003	2.83	0.17	NA	2.33
United States	2004	3.17	0.19	NA	2.63
United States	2005	3.14	0.18	NA	2.58
United States	2006	2.93	0.17	NA	2.55
United States	2007	2.70	0.15	NA	2.39
China	1995	2.55	0.16	NA	2.19
China	1996	2.62	0.14	NA	2.27
China	1997	2.63	0.14	NA	2.30
China	1998	2.71	0.14	NA	2.40
China	1999	2.77	0.15	NA	2.46
China	2000	2.82	0.15	NA	2.53
China	2001	2.92	0.15	NA	2.62
China	2002	2.91	0.15	NA	2.61
China	2003	2.99	0.16	NA	2.69
China	2004	3.07	0.16	NA	2.76
China	2005	3.10	0.16	NA	2.77
China	2006	3.09	0.16	NA	2.77
China	2007	3.08	0.16	NA	2.76
Japan	1995	2.72	0.16	NA	2.57
Japan	1996	2.73	0.16	NA	2.57
Japan	1997	2.72	0.16	NA	2.57
Japan	1998	2.72	0.16	NA	2.56
Japan	1999	2.73	0.16	NA	2.57
Japan	2000	2.76	0.16	NA	2.58
Japan	2001	2.70	0.16	NA	2.55
Japan	2002	2.83	0.17	NA	2.58
Japan	2003	2.76	0.16	NA	2.57
Japan	2004	2.72	0.16	NA	2.56
Japan	2005	2.68	0.16	NA	2.54
Japan	2006	2.69	0.16	NA	2.55
Japan	2007	2.56	0.15	NA	2.45

Country	Year	Interaction Evenness	Alatalo Interaction Evenness	H2
United States	1995	0.51	0.53	0.61
United States	1996	0.50	0.52	0.62
United States	1997	0.49	0.50	0.57
United States	1998	0.54	0.59	0.45
United States	1999	0.46	0.36	0.47
United States	2000	0.56	0.69	0.51
United States	2001	0.60	0.67	0.47
United States	2002	0.57	0.63	0.48
United States	2003	0.55	0.44	0.41
United States	2004	0.62	0.56	0.42
United States	2005	0.61	0.58	0.41
United States	2006	0.60	0.62	0.47
United States	2007	0.55	0.58	0.48
China	1995	0.53	0.63	0.34
China	1996	0.51	0.62	0.35
China	1997	0.51	0.62	0.37
China	1998	0.54	0.62	0.42
China	1999	0.55	0.62	0.43
China	2000	0.57	0.64	0.46
China	2001	0.58	0.66	0.47
China	2002	0.58	0.66	0.47
China	2003	0.60	0.68	0.50
China	2004	0.62	0.69	0.51
China	2005	0.62	0.69	0.49
China	2006	0.62	0.68	0.50
China	2007	0.62	0.66	0.50
Japan	1995	0.61	0.72	0.52
Japan	1996	0.61	0.72	0.52
Japan	1997	0.61	0.72	0.52
Japan	1998	0.61	0.72	0.52
Japan	1999	0.61	0.72	0.51
Japan	2000	0.62	0.74	0.52
Japan	2001	0.61	0.72	0.52
Japan	2002	0.62	0.76	0.47
Japan	2003	0.61	0.75	0.49
Japan	2004	0.61	0.73	0.56
Japan	2005	0.61	0.72	0.56
Japan	2006	0.61	0.72	0.55
Japan	2007	0.58	0.70	0.56

B-2. Group-Level

Table 9. Group-level Bipartite Metric Results

Group-level Bipartite Results 1 / 9

Country	Year	Number of Species HL	Number of Species LL	Mean Number of Links HL
Japan	1995	6	11	4.81
Japan	1996	6	11	4.81
Japan	1997	6	11	4.80
Japan	1998	6	11	4.80
Japan	1999	6	11	4.80
Japan	2000	6	11	4.70
Japan	2001	6	11	4.73
Japan	2002	6	11	4.64
Japan	2003	6	11	4.63
Japan	2004	6	11	4.56
Japan	2005	6	11	4.50
Japan	2006	6	11	4.50
Japan	2007	6	11	4.43
United States	1995	6	9	3.47
United States	1996	6	9	3.61
United States	1997	7	9	3.54
United States	1998	7	9	3.57
United States	1999	7	10	3.95
United States	2000	7	8	3.37
United States	2001	7	10	3.64
United States	2002	7	10	3.41
United States	2003	7	10	4.14
United States	2004	7	10	4.56
United States	2005	7	10	4.27
United States	2006	7	10	3.89
United States	2007	8	10	3.96
China	1995	8	8	3.56
China	1996	8	11	3.62
China	1997	8	11	3.62
China	1998	8	11	3.64
China	1999	8	11	3.70
China	2000	8	11	3.74
China	2001	8	11	4.06
China	2002	8	11	4.04
China	2003	8	11	4.34
China	2004	8	11	4.50
China	2005	8	11	4.39
China	2006	8	11	4.42
China	2007	8	11	4.42
United States	2008	8	10	3.79
United States	2009	8	10	4.78
United States	2010	8	10	4.04
United States	2011	7	10	4.25
United States	2012	6	10	4.22
United States	2013	5	9	4.06
United States	2014	5	9	4.30

Country	Year	Mean Number of Links LL	Mean Number of Shared Partners HL
Japan	1995	4.50	2.60
Japan	1996	4.50	2.60
Japan	1997	4.50	2.60
Japan	1998	4.50	2.60
Japan	1999	4.50	2.60
Japan	2000	4.51	2.60
Japan	2001	4.51	2.60
Japan	2002	4.59	2.60
Japan	2003	4.54	2.60
Japan	2004	4.54	2.60
Japan	2005	4.53	2.60
Japan	2006	4.53	2.60
Japan	2007	4.56	2.60
United States	1995	4.63	2.00
United States	1996	4.61	2.07
United States	1997	5.65	2.24
United States	1998	5.69	2.29
United States	1999	5.62	2.29
United States	2000	5.52	2.05
United States	2001	5.42	2.38
United States	2002	5.62	2.29
United States	2003	5.53	2.29
United States	2004	5.13	2.29
United States	2005	5.35	2.29
United States	2006	5.40	2.29
United States	2007	6.26	2.36
China	1995	5.97	1.75
China	1996	5.96	1.89
China	1997	5.94	1.89
China	1998	6.29	2.11
China	1999	6.40	2.29
China	2000	6.33	2.29
China	2001	6.32	2.50
China	2002	6.33	2.50
China	2003	6.24	2.50
China	2004	6.07	2.50
China	2005	6.05	2.50
China	2006	6.01	2.50
China	2007	5.97	2.50
United States	2008	6.34	2.64
United States	2009	6.11	2.79
United States	2010	6.35	2.75
United States	2011	5.57	2.76
United States	2012	4.77	2.73
United States	2013	4.02	2.90
United States	2014	3.96	2.90

Country	Year	Mean Number of Shared Partners LL	Cluster Coefficient HL	Cluster Coefficient LL
Japan	1995	1.07	0.44	0.75
Japan	1996	1.07	0.44	0.75
Japan	1997	1.07	0.44	0.75
Japan	1998	1.07	0.44	0.75
Japan	1999	1.07	0.44	0.75
Japan	2000	1.07	0.43	0.75
Japan	2001	1.07	0.43	0.75
Japan	2002	1.07	0.42	0.76
Japan	2003	1.07	0.42	0.76
Japan	2004	1.07	0.41	0.76
Japan	2005	1.07	0.41	0.75
Japan	2006	1.07	0.41	0.75
Japan	2007	1.07	0.40	0.76
United States	1995	1.03	0.39	0.77
United States	1996	1.14	0.40	0.77
United States	1997	1.17	0.39	0.81
United States	1998	1.31	0.40	0.81
United States	1999	1.18	0.39	0.80
United States	2000	1.21	0.42	0.79
United States	2001	1.29	0.36	0.77
United States	2002	1.16	0.34	0.80
United States	2003	1.22	0.41	0.79
United States	2004	1.22	0.46	0.73
United States	2005	1.22	0.43	0.76
United States	2006	1.22	0.39	0.77
United States	2007	1.38	0.40	0.78
China	1995	1.32	0.44	0.75
China	1996	0.93	0.33	0.74
China	1997	0.93	0.33	0.74
China	1998	0.95	0.33	0.79
China	1999	1.07	0.34	0.80
China	2000	1.07	0.34	0.79
China	2001	1.20	0.37	0.79
China	2002	1.20	0.37	0.79
China	2003	1.20	0.39	0.78
China	2004	1.20	0.41	0.76
China	2005	1.20	0.40	0.76
China	2006	1.20	0.40	0.75
China	2007	1.20	0.40	0.75
United States	2008	1.60	0.38	0.79
United States	2009	1.84	0.48	0.76
United States	2010	1.84	0.40	0.79
United States	2011	1.33	0.43	0.80
United States	2012	1.36	0.42	0.80
United States	2013	1.28	0.45	0.80
United States	2014	1.28	0.48	0.79

Country	Year	Weighted Cluster Coefficient HL	Weighted Cluster Coefficient LL	Niche Overalp HL
Japan	1995	0.56	0.86	0.40
Japan	1996	0.56	0.86	0.40
Japan	1997	0.56	0.86	0.40
Japan	1998	0.56	0.86	0.40
Japan	1999	0.56	0.86	0.40
Japan	2000	0.56	0.86	0.40
Japan	2001	0.56	0.86	0.40
Japan	2002	0.57	0.86	0.40
Japan	2003	0.57	0.86	0.40
Japan	2004	0.58	0.86	0.40
Japan	2005	0.58	0.85	0.40
Japan	2006	0.58	0.85	0.40
Japan	2007	0.58	0.85	0.40
United States	1995	0.55	0.55	0.32
United States	1996	0.59	0.56	0.32
United States	1997	0.72	0.66	0.40
United States	1998	0.75	0.71	0.40
United States	1999	0.65	0.70	0.40
United States	2000	0.72	0.59	0.40
United States	2001	0.70	0.70	0.40
United States	2002	0.67	0.68	0.40
United States	2003	0.66	0.71	0.40
United States	2004	0.61	0.71	0.40
United States	2005	0.64	0.71	0.40
United States	2006	0.65	0.68	0.40
United States	2007	0.72	0.73	0.40
China	1995	0.71	0.51	0.44
China	1996	0.58	0.58	0.44
China	1997	0.57	0.58	0.44
China	1998	0.57	0.56	0.45
China	1999	0.61	0.68	0.45
China	2000	0.60	0.68	0.44
China	2001	0.63	0.73	0.45
China	2002	0.63	0.73	0.45
China	2003	0.60	0.74	0.45
China	2004	0.60	0.75	0.45
China	2005	0.61	0.75	0.45
China	2006	0.60	0.75	0.45
China	2007	0.60	0.75	0.45
United States	2008	0.80	0.79	0.41
United States	2009	0.85	0.84	0.47
United States	2010	0.87	0.81	0.44
United States	2011	0.72	0.89	0.41
United States	2012	0.74	0.88	0.45
United States	2013	0.62	0.95	0.57
United States	2014	0.60	0.95	0.57

Country	Year	Niche Overlap LL	Togetherness HL	Togetherness LL	C Score HL	C Score LL	V Ratio HL
Japan	1995	0.25	0.36	0.16	0.23	0.52	0.61
Japan	1996	0.25	0.36	0.16	0.23	0.52	0.61
Japan	1997	0.25	0.36	0.16	0.23	0.52	0.61
Japan	1998	0.25	0.36	0.16	0.23	0.52	0.61
Japan	1999	0.25	0.36	0.16	0.23	0.52	0.61
Japan	2000	0.25	0.36	0.16	0.23	0.52	0.61
Japan	2001	0.25	0.36	0.16	0.23	0.52	0.61
Japan	2002	0.25	0.36	0.16	0.23	0.52	0.61
Japan	2003	0.25	0.36	0.16	0.23	0.52	0.61
Japan	2004	0.24	0.36	0.16	0.23	0.52	0.61
Japan	2005	0.24	0.36	0.16	0.23	0.52	0.61
Japan	2006	0.24	0.36	0.16	0.23	0.52	0.61
Japan	2007	0.23	0.36	0.16	0.23	0.52	0.61
United States	1995	0.28	0.37	0.17	0.29	0.49	0.96
United States	1996	0.31	0.35	0.19	0.29	0.48	1.03
United States	1997	0.26	0.43	0.13	0.21	0.52	0.71
United States	1998	0.30	0.40	0.16	0.24	0.47	0.97
United States	1999	0.25	0.39	0.15	0.22	0.47	1.33
United States	2000	0.28	0.42	0.13	0.22	0.55	0.41
United States	2001	0.26	0.38	0.16	0.20	0.43	1.53
United States	2002	0.25	0.40	0.15	0.21	0.46	1.15
United States	2003	0.28	0.38	0.17	0.21	0.41	1.69
United States	2004	0.31	0.38	0.17	0.21	0.41	1.69
United States	2005	0.29	0.38	0.17	0.21	0.41	1.69
United States	2006	0.25	0.38	0.17	0.21	0.41	1.69
United States	2007	0.26	0.38	0.16	0.19	0.41	1.69
China	1995	0.27	0.35	0.16	0.21	0.41	1.48
China	1996	0.19	0.33	0.12	0.20	0.50	1.50
China	1997	0.20	0.33	0.12	0.20	0.50	1.50
China	1998	0.20	0.38	0.11	0.20	0.52	1.20
China	1999	0.21	0.39	0.12	0.19	0.49	1.16
China	2000	0.21	0.39	0.12	0.19	0.49	1.16
China	2001	0.24	0.41	0.13	0.18	0.49	1.06
China	2002	0.24	0.41	0.13	0.18	0.49	1.06
China	2003	0.23	0.41	0.13	0.18	0.49	1.06
China	2004	0.23	0.41	0.13	0.18	0.49	1.06
China	2005	0.23	0.41	0.13	0.18	0.49	1.06
China	2006	0.23	0.41	0.13	0.18	0.49	1.06
China	2007	0.23	0.41	0.13	0.18	0.49	1.06
United States	2008	0.24	0.39	0.16	0.19	0.43	1.38
United States	2009	0.33	0.36	0.18	0.20	0.43	1.71
United States	2010	0.27	0.36	0.18	0.21	0.43	1.68
United States	2011	0.27	0.44	0.16	0.20	0.53	0.53
United States	2012	0.29	0.36	0.17	0.24	0.47	1.03
United States	2013	0.34	0.41	0.16	0.21	0.33	1.35
United States	2014	0.39	0.41	0.16	0.21	0.33	1.35

Country	Year	V Ratio LL	Discrepancy HL	Discrepancy LL	Extinction Slope HL
Japan	1995	1.95	9	7	5.54
Japan	1996	1.95	9	7	6.13
Japan	1997	1.95	9	7	6.11
Japan	1998	1.95	9	7	6.29
Japan	1999	1.95	9	7	5.51
Japan	2000	1.95	9	7	5.50
Japan	2001	1.95	9	7	6.71
Japan	2002	1.95	9	7	6.92
Japan	2003	1.95	9	7	5.28
Japan	2004	1.95	9	7	6.42
Japan	2005	1.95	9	7	5.60
Japan	2006	1.95	9	7	5.41
Japan	2007	1.95	9	7	6.27
United States	1995	1.98	6	4	1.00
United States	1996	1.80	5	4	4.65
United States	1997	2.73	6	4	3.98
United States	1998	2.55	6	4	4.75
United States	1999	2.64	8	5	4.36
United States	2000	2.46	9	6	4.43
United States	2001	2.60	8	5	4.88
United States	2002	2.61	8	5	5.03
United States	2003	2.71	7	4	4.05
United States	2004	2.71	7	5	4.62
United States	2005	2.71	7	5	4.47
United States	2006	2.71	7	5	4.42
United States	2007	3.24	8	6	4.57
China	1995	2.93	6	4	4.00
China	1996	3.01	10	5	3.93
China	1997	3.01	10	5	4.14
China	1998	3.29	10	6	3.81
China	1999	3.22	9	7	4.76
China	2000	3.22	9	7	4.45
China	2001	3.21	9	7	5.17
China	2002	3.21	9	7	5.87
China	2003	3.21	9	7	4.99
China	2004	3.21	9	7	4.49
China	2005	3.21	9	7	4.88
China	2006	3.21	9	7	4.67
China	2007	3.21	9	7	4.79
United States	2008	3.02	8	6	5.28
United States	2009	2.82	8	6	5.61
United States	2010	2.70	9	8	5.42
United States	2011	2.71	7	6	5.87
United States	2012	1.94	7	5	5.28
United States	2013	2.17	4	4	6.57
United States	2014	2.17	4	4	5.91

Country	Year	Extinction Slope LL	Robustness HL	Robustness LL
Japan	1995	2.25	0.85	0.69
Japan	1996	2.41	0.86	0.70
Japan	1997	2.44	0.86	0.70
Japan	1998	2.45	0.86	0.70
Japan	1999	2.25	0.84	0.69
Japan	2000	2.38	0.84	0.70
Japan	2001	2.44	0.87	0.70
Japan	2002	2.56	0.87	0.71
Japan	2003	2.46	0.84	0.70
Japan	2004	2.43	0.86	0.71
Japan	2005	2.55	0.84	0.71
Japan	2006	2.36	0.84	0.70
Japan	2007	2.50	0.86	0.71
United States	1995	2.21	0.82	0.67
United States	1996	2.46	0.82	0.71
United States	1997	2.53	0.80	0.71
United States	1998	2.70	0.83	0.72
United States	1999	2.32	0.81	0.69
United States	2000	2.65	0.81	0.71
United States	2001	2.58	0.83	0.71
United States	2002	2.30	0.83	0.68
United States	2003	2.45	0.80	0.70
United States	2004	2.34	0.82	0.69
United States	2005	2.37	0.81	0.69
United States	2006	2.47	0.81	0.70
United States	2007	2.73	0.82	0.72
China	1995	2.53	0.79	0.71
China	1996	1.89	0.79	0.65
China	1997	2.07	0.79	0.67
China	1998	1.98	0.79	0.66
China	1999	2.18	0.82	0.68
China	2000	2.08	0.81	0.67
China	2001	2.63	0.83	0.72
China	2002	2.57	0.85	0.71
China	2003	2.44	0.83	0.70
China	2004	2.40	0.82	0.70
China	2005	2.39	0.83	0.70
China	2006	2.53	0.82	0.71
China	2007	2.53	0.83	0.71
United States	2008	3.13	0.84	0.74
United States	2009	3.74	0.85	0.77
United States	2010	3.73	0.84	0.77
United States	2011	2.96	0.86	0.73
United States	2012	2.78	0.84	0.72
United States	2013	2.53	0.87	0.71
United States	2014	2.41	0.86	0.71

Country	Year	Functional Complementarity HL	Functional Complementarity LL
Japan	1995	7.32	8.57
Japan	1996	7.69	9.00
Japan	1997	8.07	9.45
Japan	1998	8.46	9.88
Japan	1999	8.89	10.42
Japan	2000	10.03	12.18
Japan	2001	7.76	9.75
Japan	2002	10.05	12.05
Japan	2003	10.95	12.78
Japan	2004	12.16	13.94
Japan	2005	12.52	14.61
Japan	2006	13.74	15.49
Japan	2007	15.93	17.76
United States	1995	25.03	25.38
United States	1996	29.85	30.45
United States	1997	20.00	19.38
United States	1998	8.51	9.51
United States	1999	12.56	12.45
United States	2000	9.08	9.92
United States	2001	11.20	11.20
United States	2002	8.04	8.19
United States	2003	8.18	8.29
United States	2004	4.65	5.00
United States	2005	4.37	4.55
United States	2006	6.86	7.06
United States	2007	7.55	8.55
China	1995	8.33	8.28
China	1996	9.31	9.36
China	1997	9.80	9.79
China	1998	10.77	10.70
China	1999	11.49	11.42
China	2000	12.30	12.23
China	2001	13.62	13.97
China	2002	13.39	13.69
China	2003	17.18	18.20
China	2004	21.02	21.62
China	2005	31.18	32.09
China	2006	36.60	38.47
China	2007	42.93	46.13
United States	2008	6253.71	7194.32
United States	2009	5259.50	5856.00
United States	2010	14740.52	14319.45
United States	2011	11106.31	11874.26
United States	2012	18397.30	19156.58
United States	2013	19686.15	19990.04
United States	2014	19431.22	21354.55

Country	Year	Partner Diversity HL	Partner Diversity LL	Generality HL	Vulnerability LL
Japan	1995	0.86	1.02	2.43	3.01
Japan	1996	0.87	1.02	2.43	3.02
Japan	1997	0.87	1.02	2.43	3.02
Japan	1998	0.86	1.02	2.42	3.02
Japan	1999	0.87	1.02	2.43	3.03
Japan	2000	0.87	1.05	2.43	3.09
Japan	2001	0.84	1.03	2.37	3.04
Japan	2002	0.88	1.09	2.47	3.18
Japan	2003	0.87	1.05	2.45	3.08
Japan	2004	0.84	1.05	2.37	3.08
Japan	2005	0.83	1.02	2.36	3.01
Japan	2006	0.84	1.03	2.37	3.02
Japan	2007	0.82	0.95	2.31	2.80
United States	1995	0.55	0.82	1.81	2.28
United States	1996	0.54	0.76	1.78	2.15
United States	1997	0.57	0.89	1.83	2.45
United States	1998	0.68	1.16	2.07	3.23
United States	1999	0.61	0.91	1.96	2.60
United States	2000	0.68	1.00	2.04	2.77
United States	2001	0.76	1.18	2.26	3.36
United States	2002	0.69	1.20	2.12	3.40
United States	2003	0.73	1.18	2.28	3.38
United States	2004	0.87	1.25	2.61	3.72
United States	2005	0.83	1.29	2.51	3.77
United States	2006	0.75	1.23	2.32	3.55
United States	2007	0.73	1.13	2.23	3.17
China	1995	0.82	0.98	2.41	2.70
China	1996	0.83	1.02	2.45	2.79
China	1997	0.82	1.03	2.42	2.84
China	1998	0.82	1.08	2.40	3.02
China	1999	0.82	1.12	2.40	3.13
China	2000	0.82	1.14	2.40	3.25
China	2001	0.84	1.19	2.42	3.43
China	2002	0.83	1.18	2.41	3.41
China	2003	0.85	1.21	2.42	3.56
China	2004	0.86	1.20	2.44	3.69
China	2005	0.87	1.20	2.47	3.72
China	2006	0.87	1.19	2.46	3.72
China	2007	0.86	1.17	2.45	3.70
United States	2008	0.68	1.00	2.07	2.79
United States	2009	0.98	1.36	2.89	4.03
United States	2010	0.74	1.20	2.26	3.39
United States	2011	0.75	1.11	2.24	3.15
United States	2012	0.67	0.89	2.08	2.52
United States	2013	0.63	0.75	1.98	2.17
United States	2014	0.68	0.89	2.14	2.52

B-3. Species-Level

Table 10. Individual-level Bipartite Metric Results

Species-level Bipartite Results 1 / 25

Country	Year	Element or Product	Degree	Normalised Degree	Species Strength	Interaction Push Pull
China	2007	Magnets	5	0.45	3.66	0.53
China	2007	Metallurgy Ex Batt	4	0.36	0.67	-0.08
China	2007	Glass Additives	6	0.55	1.45	0.08
China	2007	Fuel Cracking Catalysts	2	0.18	0.44	-0.28
China	2007	Polishing Powder	3	0.27	0.37	-0.21
China	2007	Battery Alloys	5	0.45	1.31	0.06
China	2007	Phosphors	6	0.55	2.97	0.33
China	2007	Auto Catalysts	4	0.36	0.13	-0.22
China	2007	Ce	7	0.88	3.28	0.33
China	2007	La	7	0.88	2.35	0.19
China	2007	Nd	5	0.63	1.02	0.00
China	2007	Pr	6	0.75	0.39	-0.10
China	2007	Y	2	0.25	0.71	-0.14
China	2007	Dy	1	0.13	0.05	-0.95
China	2007	Gd	2	0.25	0.04	-0.48
China	2007	Other Elements	1	0.13	0.04	-0.96
China	2007	Tb	2	0.25	0.05	-0.48
China	2007	Eu	1	0.13	0.05	-0.95
China	2007	Sm	1	0.13	0.03	-0.97
China	2006	Magnets	5	0.45	3.66	0.53
China	2006	Metallurgy Ex Batt	4	0.36	0.71	-0.07
China	2006	Glass Additives	6	0.55	1.51	0.08
China	2006	Fuel Cracking Catalysts	2	0.18	0.45	-0.27
China	2006	Polishing Powder	3	0.27	0.34	-0.22
China	2006	Battery Alloys	5	0.45	1.29	0.06
China	2006	Phosphors	6	0.55	2.93	0.32
China	2006	Auto Catalysts	4	0.36	0.11	-0.22
China	2006	Ce	7	0.88	3.28	0.33
China	2006	La	7	0.88	2.35	0.19
China	2006	Nd	5	0.63	1.02	0.00
China	2006	Pr	6	0.75	0.39	-0.10
China	2006	Y	2	0.25	0.71	-0.14
China	2006	Dy	1	0.13	0.05	-0.95
China	2006	Gd	2	0.25	0.04	-0.48
China	2006	Other Elements	1	0.13	0.04	-0.96
China	2006	Tb	2	0.25	0.05	-0.48
China	2006	Eu	1	0.13	0.05	-0.95
China	2006	Sm	1	0.13	0.03	-0.97
China	2005	Magnets	5	0.45	3.58	0.52
China	2005	Metallurgy Ex Batt	4	0.36	0.81	-0.05
China	2005	Glass Additives	6	0.55	1.50	0.08
China	2005	Fuel Cracking Catalysts	2	0.18	0.46	-0.27
China	2005	Polishing Powder	3	0.27	0.32	-0.23
China	2005	Battery Alloys	5	0.45	1.27	0.05
China	2005	Phosphors	6	0.55	2.95	0.33

Country	Year	Element or Product	Degree	Normalised Degree	Species Strength	Interaction Push Pull
China	2005	Auto Catalysts	4	0.36	0.11	-0.22
China	2005	Ce	7	0.88	3.26	0.32
China	2005	La	7	0.88	2.35	0.19
China	2005	Nd	5	0.63	1.02	0.00
China	2005	Pr	6	0.75	0.39	-0.10
China	2005	Y	2	0.25	0.71	-0.14
China	2005	Dy	1	0.13	0.05	-0.95
China	2005	Gd	2	0.25	0.04	-0.48
China	2005	Other Elements	1	0.13	0.04	-0.96
China	2005	Tb	2	0.25	0.05	-0.48
China	2005	Sm	1	0.13	0.03	-0.97
China	2005	Eu	1	0.13	0.05	-0.95
China	2004	Magnets	5	0.45	3.62	0.52
China	2004	Glass Additives	6	0.55	1.71	0.12
China	2004	Metallurgy Ex Batt	4	0.36	0.63	-0.09
China	2004	Fuel Cracking Catalysts	2	0.18	0.46	-0.27
China	2004	Polishing Powder	3	0.27	0.30	-0.23
China	2004	Battery Alloys	5	0.45	1.26	0.05
China	2004	Phosphors	6	0.55	2.91	0.32
China	2004	Auto Catalysts	4	0.36	0.10	-0.22
China	2004	Ce	7	0.88	3.27	0.32
China	2004	La	7	0.88	2.35	0.19
China	2004	Nd	5	0.63	1.03	0.01
China	2004	Pr	6	0.75	0.39	-0.10
China	2004	Y	2	0.25	0.71	-0.14
China	2004	Dy	1	0.13	0.05	-0.95
China	2004	Other Elements	1	0.13	0.04	-0.96
China	2004	Gd	2	0.25	0.03	-0.48
China	2004	Eu	1	0.13	0.05	-0.95
China	2004	Tb	2	0.25	0.05	-0.48
China	2004	Sm	1	0.13	0.03	-0.97
China	2003	Glass Additives	6	0.55	1.80	0.13
China	2003	Metallurgy Ex Batt	4	0.36	0.82	-0.05
China	2003	Magnets	5	0.45	3.49	0.50
China	2003	Fuel Cracking Catalysts	2	0.18	0.57	-0.22
China	2003	Polishing Powder	3	0.27	0.21	-0.26
China	2003	Battery Alloys	5	0.45	1.19	0.04
China	2003	Phosphors	6	0.55	2.86	0.31
China	2003	Auto Catalysts	4	0.36	0.07	-0.23
China	2003	Ce	7	0.88	3.26	0.32
China	2003	La	7	0.88	2.35	0.19
China	2003	Nd	5	0.63	1.03	0.01
China	2003	Pr	6	0.75	0.38	-0.10
China	2003	Y	2	0.25	0.71	-0.14
China	2003	Dy	1	0.13	0.05	-0.95
China	2003	Other Elements	1	0.13	0.04	-0.96
China	2003	Gd	2	0.25	0.04	-0.48
China	2003	Tb	2	0.25	0.05	-0.48
China	2003	Sm	1	0.13	0.03	-0.97
China	2003	Eu	1	0.13	0.05	-0.95
China	2002	Metallurgy Ex Batt	4	0.36	1.17	0.04

Country	Year	Element or Product	Degree	Normalised Degree	Species Strength	Interaction Push Pull
China	2002	Fuel Cracking Catalysts	2	0.18	0.65	-0.17
China	2002	Magnets	5	0.45	3.49	0.50
China	2002	Glass Additives	6	0.55	1.55	0.09
China	2002	Polishing Powder	3	0.27	0.18	-0.27
China	2002	Battery Alloys	5	0.45	1.15	0.03
China	2002	Phosphors	6	0.55	2.73	0.29
China	2002	Auto Catalysts	4	0.36	0.07	-0.23
China	2002	La	7	0.88	2.36	0.19
China	2002	Ce	7	0.88	3.26	0.32
China	2002	Nd	5	0.63	1.02	0.00
China	2002	Pr	6	0.75	0.39	-0.10
China	2002	Y	2	0.25	0.71	-0.14
China	2002	Dy	1	0.13	0.05	-0.95
China	2002	Other Elements	1	0.13	0.04	-0.96
China	2002	Gd	2	0.25	0.04	-0.48
China	2002	Eu	1	0.13	0.06	-0.94
China	2002	Tb	2	0.25	0.04	-0.48
China	2002	Sm	1	0.13	0.03	-0.97
China	2001	Metallurgy Ex Batt	4	0.36	1.16	0.04
China	2001	Fuel Cracking Catalysts	2	0.18	0.64	-0.18
China	2001	Magnets	5	0.45	3.53	0.51
China	2001	Glass Additives	6	0.55	1.55	0.09
China	2001	Polishing Powder	3	0.27	0.18	-0.27
China	2001	Battery Alloys	5	0.45	1.15	0.03
China	2001	Phosphors	6	0.55	2.71	0.28
China	2001	Auto Catalysts	4	0.36	0.07	-0.23
China	2001	La	7	0.88	2.37	0.20
China	2001	Ce	7	0.88	3.26	0.32
China	2001	Nd	5	0.63	1.02	0.00
China	2001	Pr	6	0.75	0.39	-0.10
China	2001	Y	2	0.25	0.71	-0.15
China	2001	Dy	1	0.13	0.05	-0.95
China	2001	Other Elements	1	0.13	0.04	-0.96
China	2001	Gd	2	0.25	0.04	-0.48
China	2001	Eu	1	0.13	0.06	-0.94
China	2001	Tb	2	0.25	0.04	-0.48
China	2001	Sm	1	0.13	0.03	-0.97
China	2000	Metallurgy Ex Batt	4	0.36	1.33	0.08
China	2000	Fuel Cracking Catalysts	2	0.18	0.69	-0.15
China	2000	Magnets	4	0.36	3.04	0.51
China	2000	Glass Additives	6	0.55	1.46	0.08
China	2000	Polishing Powder	3	0.27	0.16	-0.28
China	2000	Battery Alloys	5	0.45	1.14	0.03
China	2000	Phosphors	6	0.55	3.11	0.35
China	2000	Auto Catalysts	3	0.27	0.05	-0.32
China	2000	La	7	0.88	2.33	0.19
China	2000	Ce	7	0.88	3.28	0.33
China	2000	Nd	5	0.63	1.04	0.01
China	2000	Pr	5	0.63	0.37	-0.13
China	2000	Y	2	0.25	0.71	-0.15
China	2000	Dy	1	0.13	0.05	-0.95

Country	Year	Element or Product	Degree	Normalised Degree	Species Strength	Interaction Push Pull
China	2000	Other Elements	1	0.13	0.04	-0.96
China	2000	Gd	2	0.25	0.05	-0.48
China	2000	Sm	1	0.13	0.04	-0.96
China	2000	Eu	1	0.13	0.05	-0.95
China	2000	Tb	1	0.13	0.05	-0.95
China	1999	Metallurgy Ex Batt	4	0.36	1.49	0.12
China	1999	Fuel Cracking Catalysts	2	0.18	0.71	-0.14
China	1999	Magnets	4	0.36	2.88	0.47
China	1999	Glass Additives	6	0.55	1.49	0.08
China	1999	Polishing Powder	3	0.27	0.14	-0.29
China	1999	Battery Alloys	5	0.45	1.11	0.02
China	1999	Phosphors	6	0.55	3.14	0.36
China	1999	Auto Catalysts	3	0.27	0.05	-0.32
China	1999	La	7	0.88	2.38	0.20
China	1999	Ce	7	0.88	3.26	0.32
China	1999	Nd	5	0.63	1.04	0.01
China	1999	Pr	5	0.63	0.37	-0.13
China	1999	Y	2	0.25	0.72	-0.14
China	1999	Dy	1	0.13	0.05	-0.95
China	1999	Other Elements	1	0.13	0.04	-0.96
China	1999	Gd	2	0.25	0.05	-0.47
China	1999	Sm	1	0.13	0.02	-0.98
China	1999	Eu	1	0.13	0.03	-0.97
China	1999	Tb	1	0.13	0.03	-0.97
China	1998	Metallurgy Ex Batt	4	0.36	1.64	0.16
China	1998	Fuel Cracking Catalysts	2	0.18	0.72	-0.14
China	1998	Glass Additives	6	0.55	1.49	0.08
China	1998	Magnets	4	0.36	3.05	0.51
China	1998	Polishing Powder	3	0.27	0.11	-0.30
China	1998	Battery Alloys	5	0.45	1.10	0.02
China	1998	Phosphors	5	0.45	2.86	0.37
China	1998	Auto Catalysts	2	0.18	0.04	-0.48
China	1998	La	7	0.88	2.38	0.20
China	1998	Ce	7	0.88	3.33	0.33
China	1998	Nd	4	0.50	0.98	-0.01
China	1998	Pr	5	0.63	0.35	-0.13
China	1998	Y	2	0.25	0.73	-0.14
China	1998	Dy	1	0.13	0.05	-0.95
China	1998	Other Elements	1	0.13	0.04	-0.96
China	1998	Gd	1	0.13	0.02	-0.98
China	1998	Sm	1	0.13	0.03	-0.97
China	1998	Eu	1	0.13	0.04	-0.96
China	1998	Tb	1	0.13	0.04	-0.96
China	1997	Metallurgy Ex Batt	4	0.36	1.87	0.22
China	1997	Fuel Cracking Catalysts	2	0.18	0.72	-0.14
China	1997	Glass Additives	6	0.55	1.57	0.10
China	1997	Magnets	4	0.36	2.85	0.46
China	1997	Polishing Powder	3	0.27	0.09	-0.30
China	1997	Battery Alloys	5	0.45	1.08	0.02
China	1997	Phosphors	5	0.45	2.79	0.36
China	1997	Auto Catalysts	1	0.09	0.02	-0.98

Country	Year	Element or Product	Degree	Normalised Degree	Species Strength	Interaction Push Pull
China	1997	La	6	0.75	2.27	0.21
China	1997	Ce	7	0.88	3.38	0.34
China	1997	Nd	4	0.50	0.98	0.00
China	1997	Pr	5	0.63	0.38	-0.12
China	1997	Y	2	0.25	0.71	-0.14
China	1997	Other Elements	1	0.13	0.04	-0.96
China	1997	Dy	1	0.13	0.05	-0.95
China	1997	Gd	1	0.13	0.02	-0.98
China	1997	Sm	1	0.13	0.05	-0.95
China	1997	Eu	1	0.13	0.06	-0.94
China	1997	Tb	1	0.13	0.06	-0.94
China	1996	Metallurgy Ex Batt	4	0.36	1.96	0.24
China	1996	Fuel Cracking Catalysts	2	0.18	0.72	-0.14
China	1996	Glass Additives	6	0.55	1.52	0.09
China	1996	Magnets	4	0.36	2.79	0.45
China	1996	Polishing Powder	3	0.27	0.08	-0.31
China	1996	Battery Alloys	5	0.45	1.08	0.02
China	1996	Phosphors	5	0.45	2.83	0.37
China	1996	Auto Catalysts	1	0.09	0.02	-0.98
China	1996	La	6	0.75	2.28	0.21
China	1996	Ce	7	0.88	3.37	0.34
China	1996	Nd	4	0.50	0.99	0.00
China	1996	Pr	5	0.63	0.40	-0.12
China	1996	Y	2	0.25	0.66	-0.17
China	1996	Other Elements	1	0.13	0.04	-0.96
China	1996	Dy	1	0.13	0.06	-0.94
China	1996	Sm	1	0.13	0.05	-0.95
China	1996	Eu	1	0.13	0.07	-0.93
China	1996	Gd	1	0.13	0.01	-0.99
China	1996	Tb	1	0.13	0.07	-0.93
China	1995	Metallurgy Ex Batt	4	0.50	2.09	0.27
China	1995	Fuel Cracking Catalysts	2	0.25	0.72	-0.14
China	1995	Glass Additives	6	0.75	1.58	0.10
China	1995	Magnets	4	0.50	2.69	0.42
China	1995	Polishing Powder	3	0.38	0.08	-0.31
China	1995	Battery Alloys	3	0.38	0.04	-0.32
China	1995	Phosphors	3	0.38	0.78	-0.07
China	1995	Auto Catalysts	1	0.13	0.02	-0.98
China	1995	La	6	0.75	2.35	0.23
China	1995	Ce	7	0.88	3.42	0.35
China	1995	Nd	4	0.50	0.96	-0.01
China	1995	Pr	4	0.50	0.36	-0.16
China	1995	Y	2	0.25	0.80	-0.10
China	1995	Other Elements	1	0.13	0.04	-0.96
China	1995	Dy	1	0.13	0.06	-0.94
China	1995	Gd	1	0.13	0.02	-0.98

Country	Year	Element or Product	Nested Rank	PDI	Resource Range	Species Specificity Index	PSI
China	2007	Magnets	0.29	0.96	0.60	0.70	0.84
China	2007	Metallurgy Ex Batt	0.57	0.91	0.70	0.55	0.21
China	2007	Glass Additives	0.00	0.95	0.50	0.67	0.24
China	2007	Fuel Cracking Catalysts	1.00	0.99	0.90	0.89	0.37
China	2007	Polishing Powder	0.86	0.95	0.80	0.69	0.18
China	2007	Battery Alloys	0.43	0.90	0.60	0.56	0.15
China	2007	Phosphors	0.14	0.96	0.50	0.67	0.75
China	2007	Auto Catalysts	0.71	0.99	0.70	0.89	0.10
China	2007	Ce	0.00	0.64	0.14	0.31	1.00
China	2007	La	0.10	0.79	0.14	0.37	1.00
China	2007	Nd	0.30	0.97	0.43	0.82	1.00
China	2007	Pr	0.20	0.97	0.29	0.78	1.00
China	2007	Y	0.40	0.99	0.86	0.94	1.00
China	2007	Dy	0.70	1.00	1.00	1.00	1.00
China	2007	Gd	0.50	0.97	0.86	0.84	1.00
China	2007	Other Elements	0.80	1.00	1.00	1.00	1.00
China	2007	Tb	0.60	0.97	0.86	0.83	1.00
China	2007	Eu	0.90	1.00	1.00	1.00	1.00
China	2007	Sm	1.00	1.00	1.00	1.00	1.00
China	2006	Magnets	0.29	0.96	0.60	0.70	0.82
China	2006	Metallurgy Ex Batt	0.57	0.91	0.70	0.55	0.23
China	2006	Glass Additives	0.00	0.95	0.50	0.67	0.26
China	2006	Fuel Cracking Catalysts	1.00	0.99	0.90	0.90	0.38
China	2006	Polishing Powder	0.86	0.95	0.80	0.69	0.16
China	2006	Battery Alloys	0.43	0.90	0.60	0.56	0.14
China	2006	Phosphors	0.14	0.96	0.50	0.67	0.74
China	2006	Auto Catalysts	0.71	0.99	0.70	0.89	0.09
China	2006	Ce	0.00	0.66	0.14	0.33	1.00
China	2006	La	0.10	0.80	0.14	0.38	1.00
China	2006	Nd	0.30	0.97	0.43	0.81	1.00
China	2006	Pr	0.20	0.96	0.29	0.77	1.00
China	2006	Y	0.40	0.99	0.86	0.93	1.00
China	2006	Dy	0.70	1.00	1.00	1.00	1.00
China	2006	Gd	0.50	0.97	0.86	0.84	1.00
China	2006	Other Elements	0.80	1.00	1.00	1.00	1.00
China	2006	Tb	0.60	0.96	0.86	0.80	1.00
China	2006	Eu	0.90	1.00	1.00	1.00	1.00
China	2006	Sm	1.00	1.00	1.00	1.00	1.00
China	2005	Magnets	0.29	0.96	0.60	0.70	0.80
China	2005	Metallurgy Ex Batt	0.57	0.91	0.70	0.55	0.25
China	2005	Glass Additives	0.00	0.95	0.50	0.67	0.25
China	2005	Fuel Cracking Catalysts	1.00	0.99	0.90	0.90	0.38
China	2005	Polishing Powder	0.86	0.95	0.80	0.69	0.15
China	2005	Battery Alloys	0.43	0.90	0.60	0.56	0.13
China	2005	Phosphors	0.14	0.96	0.50	0.67	0.74

Country	Year	Element or Product	Nested Rank	PDI	Resource Range	Species Specificity Index	PSI
China	2005	Auto Catalysts	0.71	0.99	0.70	0.89	0.08
China	2005	Ce	0.00	0.71	0.14	0.35	1.00
China	2005	La	0.10	0.80	0.14	0.39	1.00
China	2005	Nd	0.30	0.96	0.43	0.79	1.00
China	2005	Pr	0.20	0.96	0.29	0.74	1.00
China	2005	Y	0.40	0.99	0.86	0.92	1.00
China	2005	Dy	0.70	1.00	1.00	1.00	1.00
China	2005	Gd	0.50	0.97	0.86	0.84	1.00
China	2005	Other Elements	0.80	1.00	1.00	1.00	1.00
China	2005	Tb	0.60	0.97	0.86	0.83	1.00
China	2005	Sm	0.90	1.00	1.00	1.00	1.00
China	2005	Eu	1.00	1.00	1.00	1.00	1.00
China	2004	Magnets	0.29	0.96	0.60	0.70	0.82
China	2004	Glass Additives	0.00	0.95	0.50	0.67	0.34
China	2004	Metallurgy Ex Batt	0.57	0.91	0.70	0.55	0.19
China	2004	Fuel Cracking Catalysts	1.00	0.99	0.90	0.90	0.38
China	2004	Polishing Powder	0.86	0.95	0.80	0.69	0.14
China	2004	Battery Alloys	0.43	0.90	0.60	0.56	0.12
China	2004	Phosphors	0.14	0.96	0.50	0.67	0.71
China	2004	Auto Catalysts	0.71	0.99	0.70	0.89	0.08
China	2004	Ce	0.00	0.77	0.14	0.37	1.00
China	2004	La	0.10	0.80	0.14	0.39	1.00
China	2004	Nd	0.30	0.97	0.43	0.80	1.00
China	2004	Pr	0.20	0.96	0.29	0.76	1.00
China	2004	Y	0.40	0.98	0.86	0.89	1.00
China	2004	Dy	0.70	1.00	1.00	1.00	1.00
China	2004	Other Elements	0.80	1.00	1.00	1.00	1.00
China	2004	Gd	0.50	0.98	0.86	0.87	1.00
China	2004	Eu	0.90	1.00	1.00	1.00	1.00
China	2004	Tb	0.60	0.98	0.86	0.85	1.00
China	2004	Sm	1.00	1.00	1.00	1.00	1.00
China	2003	Glass Additives	0.00	0.95	0.50	0.67	0.36
China	2003	Metallurgy Ex Batt	0.57	0.91	0.70	0.55	0.24
China	2003	Magnets	0.29	0.96	0.60	0.70	0.75
China	2003	Fuel Cracking Catalysts	1.00	0.99	0.90	0.90	0.47
China	2003	Polishing Powder	0.86	0.95	0.80	0.69	0.10
China	2003	Battery Alloys	0.43	0.90	0.60	0.56	0.09
China	2003	Phosphors	0.14	0.96	0.50	0.67	0.68
China	2003	Auto Catalysts	0.71	0.99	0.70	0.88	0.05
China	2003	Ce	0.00	0.80	0.14	0.43	1.00
China	2003	La	0.10	0.87	0.14	0.48	1.00
China	2003	Nd	0.30	0.95	0.43	0.73	1.00
China	2003	Pr	0.20	0.95	0.29	0.70	1.00
China	2003	Y	0.40	0.98	0.86	0.85	1.00
China	2003	Dy	0.70	1.00	1.00	1.00	1.00
China	2003	Other Elements	0.80	1.00	1.00	1.00	1.00
China	2003	Gd	0.50	0.97	0.86	0.81	1.00
China	2003	Tb	0.60	0.96	0.86	0.80	1.00
China	2003	Sm	0.90	1.00	1.00	1.00	1.00
China	2003	Eu	1.00	1.00	1.00	1.00	1.00
China	2002	Metallurgy Ex Batt	0.57	0.91	0.70	0.55	0.34

Country	Year	Element or Product	Nested Rank	PDI	Resource Range	Species Specificity Index	PSI
China	2002	Fuel Cracking Catalysts	1.00	0.99	0.90	0.89	0.53
China	2002	Magnets	0.29	0.96	0.60	0.70	0.68
China	2002	Glass Additives	0.00	0.95	0.50	0.67	0.26
China	2002	Polishing Powder	0.86	0.95	0.80	0.69	0.08
China	2002	Battery Alloys	0.43	0.90	0.60	0.57	0.08
China	2002	Phosphors	0.14	0.96	0.50	0.67	0.70
China	2002	Auto Catalysts	0.71	0.99	0.70	0.87	0.05
China	2002	La	0.00	0.90	0.14	0.56	1.00
China	2002	Ce	0.10	0.81	0.14	0.43	1.00
China	2002	Nd	0.30	0.93	0.43	0.68	1.00
China	2002	Pr	0.20	0.92	0.29	0.65	1.00
China	2002	Y	0.40	0.98	0.86	0.87	1.00
China	2002	Dy	0.70	1.00	1.00	1.00	1.00
China	2002	Other Elements	0.80	1.00	1.00	1.00	1.00
China	2002	Gd	0.50	0.97	0.86	0.83	1.00
China	2002	Eu	0.90	1.00	1.00	1.00	1.00
China	2002	Tb	0.60	0.93	0.86	0.70	1.00
China	2002	Sm	1.00	1.00	1.00	1.00	1.00
China	2001	Metallurgy Ex Batt	0.57	0.91	0.70	0.55	0.34
China	2001	Fuel Cracking Catalysts	1.00	0.99	0.90	0.89	0.52
China	2001	Magnets	0.29	0.96	0.60	0.70	0.69
China	2001	Glass Additives	0.00	0.95	0.50	0.67	0.26
China	2001	Polishing Powder	0.86	0.95	0.80	0.69	0.08
China	2001	Battery Alloys	0.43	0.90	0.60	0.56	0.08
China	2001	Phosphors	0.14	0.95	0.50	0.67	0.69
China	2001	Auto Catalysts	0.71	0.99	0.70	0.87	0.05
China	2001	La	0.00	0.89	0.14	0.55	1.00
China	2001	Ce	0.10	0.81	0.14	0.43	1.00
China	2001	Nd	0.30	0.93	0.43	0.68	1.00
China	2001	Pr	0.20	0.93	0.29	0.66	1.00
China	2001	Y	0.40	0.98	0.86	0.87	1.00
China	2001	Dy	0.70	1.00	1.00	1.00	1.00
China	2001	Other Elements	0.80	1.00	1.00	1.00	1.00
China	2001	Gd	0.50	0.98	0.86	0.85	1.00
China	2001	Eu	0.90	1.00	1.00	1.00	1.00
China	2001	Tb	0.60	0.93	0.86	0.70	1.00
China	2001	Sm	1.00	1.00	1.00	1.00	1.00
China	2000	Metallurgy Ex Batt	0.43	0.91	0.70	0.55	0.38
China	2000	Fuel Cracking Catalysts	1.00	0.99	0.90	0.90	0.56
China	2000	Magnets	0.57	0.96	0.70	0.71	0.65
China	2000	Glass Additives	0.00	0.95	0.50	0.67	0.22
China	2000	Polishing Powder	0.71	0.95	0.80	0.70	0.07
China	2000	Battery Alloys	0.29	0.90	0.60	0.55	0.08
China	2000	Phosphors	0.14	0.96	0.50	0.67	0.73
China	2000	Auto Catalysts	0.86	0.99	0.80	0.91	0.04
China	2000	La	0.00	0.91	0.14	0.59	1.00
China	2000	Ce	0.10	0.85	0.14	0.47	1.00
China	2000	Nd	0.20	0.92	0.43	0.65	1.00
China	2000	Pr	0.30	0.91	0.43	0.63	1.00
China	2000	Y	0.40	0.98	0.86	0.89	1.00
China	2000	Dy	0.60	1.00	1.00	1.00	1.00

Country	Year	Element or Product	Nested Rank	PDI	Resource Range	Species Specificity Index	PSI
China	2000	Other Elements	0.70	1.00	1.00	1.00	1.00
China	2000	Gd	0.50	0.96	0.86	0.80	1.00
China	2000	Sm	0.80	1.00	1.00	1.00	1.00
China	2000	Eu	0.90	1.00	1.00	1.00	1.00
China	2000	Tb	1.00	1.00	1.00	1.00	1.00
China	1999	Metallurgy Ex Batt	0.43	0.91	0.70	0.55	0.41
China	1999	Fuel Cracking Catalysts	1.00	0.99	0.90	0.90	0.57
China	1999	Magnets	0.57	0.96	0.70	0.70	0.59
China	1999	Glass Additives	0.00	0.95	0.50	0.67	0.21
China	1999	Polishing Powder	0.71	0.95	0.80	0.69	0.06
China	1999	Battery Alloys	0.29	0.90	0.60	0.57	0.06
China	1999	Phosphors	0.14	0.96	0.50	0.68	0.69
China	1999	Auto Catalysts	0.86	0.99	0.80	0.89	0.04
China	1999	La	0.00	0.92	0.14	0.61	1.00
China	1999	Ce	0.10	0.87	0.14	0.50	1.00
China	1999	Nd	0.20	0.89	0.43	0.63	1.00
China	1999	Pr	0.30	0.89	0.43	0.61	1.00
China	1999	Y	0.40	0.98	0.86	0.87	1.00
China	1999	Dy	0.60	1.00	1.00	1.00	1.00
China	1999	Other Elements	0.70	1.00	1.00	1.00	1.00
China	1999	Gd	0.50	0.95	0.86	0.76	1.00
China	1999	Sm	0.80	1.00	1.00	1.00	1.00
China	1999	Eu	0.90	1.00	1.00	1.00	1.00
China	1999	Tb	1.00	1.00	1.00	1.00	1.00
China	1998	Metallurgy Ex Batt	0.43	0.91	0.70	0.55	0.44
China	1998	Fuel Cracking Catalysts	0.86	0.99	0.90	0.90	0.58
China	1998	Glass Additives	0.00	0.95	0.50	0.67	0.21
China	1998	Magnets	0.57	0.96	0.70	0.70	0.56
China	1998	Polishing Powder	0.71	0.95	0.80	0.70	0.05
China	1998	Battery Alloys	0.14	0.91	0.60	0.57	0.06
China	1998	Phosphors	0.29	0.96	0.60	0.69	0.69
China	1998	Auto Catalysts	1.00	0.99	0.90	0.93	0.03
China	1998	La	0.00	0.92	0.14	0.62	1.00
China	1998	Ce	0.10	0.88	0.14	0.53	1.00
China	1998	Nd	0.30	0.87	0.57	0.62	1.00
China	1998	Pr	0.20	0.87	0.43	0.61	1.00
China	1998	Y	0.40	0.97	0.86	0.84	1.00
China	1998	Dy	0.50	1.00	1.00	1.00	1.00
China	1998	Other Elements	0.60	1.00	1.00	1.00	1.00
China	1998	Gd	0.70	1.00	1.00	1.00	1.00
China	1998	Sm	0.80	1.00	1.00	1.00	1.00
China	1998	Eu	0.90	1.00	1.00	1.00	1.00
China	1998	Tb	1.00	1.00	1.00	1.00	1.00
China	1997	Metallurgy Ex Batt	0.43	0.91	0.70	0.55	0.49
China	1997	Fuel Cracking Catalysts	0.86	0.99	0.90	0.89	0.58
China	1997	Glass Additives	0.00	0.95	0.50	0.67	0.21
China	1997	Magnets	0.57	0.96	0.70	0.70	0.47
China	1997	Polishing Powder	0.71	0.95	0.80	0.69	0.04
China	1997	Battery Alloys	0.14	0.90	0.60	0.55	0.07
China	1997	Phosphors	0.29	0.95	0.60	0.67	0.67
China	1997	Auto Catalysts	1.00	1.00	1.00	1.00	0.02

Country	Year	Element or Product	Nested Rank	PDI	Resource Range	Species Specificity Index	PSI
China	1997	La	0.10	0.92	0.29	0.63	1.00
China	1997	Ce	0.00	0.90	0.14	0.57	1.00
China	1997	Nd	0.30	0.87	0.57	0.62	1.00
China	1997	Pr	0.20	0.86	0.43	0.60	1.00
China	1997	Y	0.40	0.96	0.86	0.78	1.00
China	1997	Other Elements	0.50	1.00	1.00	1.00	1.00
China	1997	Dy	0.60	1.00	1.00	1.00	1.00
China	1997	Gd	0.70	1.00	1.00	1.00	1.00
China	1997	Sm	0.80	1.00	1.00	1.00	1.00
China	1997	Eu	0.90	1.00	1.00	1.00	1.00
China	1997	Tb	1.00	1.00	1.00	1.00	1.00
China	1996	Metallurgy Ex Batt	0.43	0.91	0.70	0.55	0.51
China	1996	Fuel Cracking Catalysts	0.86	0.99	0.90	0.90	0.58
China	1996	Glass Additives	0.00	0.95	0.50	0.67	0.21
China	1996	Magnets	0.57	0.96	0.70	0.70	0.44
China	1996	Polishing Powder	0.71	0.95	0.80	0.69	0.03
China	1996	Battery Alloys	0.14	0.90	0.60	0.54	0.07
China	1996	Phosphors	0.29	0.94	0.60	0.63	0.67
China	1996	Auto Catalysts	1.00	1.00	1.00	1.00	0.02
China	1996	La	0.10	0.92	0.29	0.63	1.00
China	1996	Ce	0.00	0.91	0.14	0.59	1.00
China	1996	Nd	0.30	0.89	0.57	0.63	1.00
China	1996	Pr	0.20	0.88	0.43	0.60	1.00
China	1996	Y	0.40	0.97	0.86	0.81	1.00
China	1996	Other Elements	0.50	1.00	1.00	1.00	1.00
China	1996	Dy	0.60	1.00	1.00	1.00	1.00
China	1996	Sm	0.70	1.00	1.00	1.00	1.00
China	1996	Eu	0.80	1.00	1.00	1.00	1.00
China	1996	Gd	0.90	1.00	1.00	1.00	1.00
China	1996	Tb	1.00	1.00	1.00	1.00	1.00
China	1995	Metallurgy Ex Batt	0.14	0.87	0.57	0.53	0.52
China	1995	Fuel Cracking Catalysts	0.86	0.98	0.86	0.89	0.59
China	1995	Glass Additives	0.00	0.93	0.29	0.66	0.21
China	1995	Magnets	0.29	0.93	0.57	0.68	0.39
China	1995	Polishing Powder	0.43	0.92	0.71	0.66	0.03
China	1995	Battery Alloys	0.57	0.88	0.71	0.60	0.02
China	1995	Phosphors	0.71	0.96	0.71	0.76	0.61
China	1995	Auto Catalysts	1.00	1.00	1.00	1.00	0.02
China	1995	La	0.14	0.92	0.29	0.64	1.00
China	1995	Ce	0.00	0.91	0.14	0.60	1.00
China	1995	Nd	0.29	0.91	0.57	0.65	1.00
China	1995	Pr	0.43	0.90	0.57	0.64	1.00
China	1995	Y	0.57	0.96	0.86	0.78	1.00
China	1995	Other Elements	0.71	1.00	1.00	1.00	1.00
China	1995	Dy	0.86	1.00	1.00	1.00	1.00
China	1995	Gd	1.00	1.00	1.00	1.00	1.00

Country	Year	Element or Product	NSI	Betweenness	Weighted Betweenness	Closeness
China	2007	Magnets	1.14	0.00	0.00	0.12
China	2007	Metallurgy Ex Batt	1.00	0.17	0.60	0.13
China	2007	Glass Additives	1.00	0.17	0.40	0.13
China	2007	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	2007	Polishing Powder	1.00	0.17	0.00	0.13
China	2007	Battery Alloys	1.00	0.17	0.00	0.13
China	2007	Phosphors	1.00	0.17	0.00	0.13
China	2007	Auto Catalysts	1.00	0.17	0.00	0.13
China	2007	Ce	1.10	0.16	0.40	0.10
China	2007	La	1.10	0.16	0.11	0.10
China	2007	Nd	1.10	0.20	0.39	0.10
China	2007	Pr	1.10	0.20	0.00	0.10
China	2007	Y	1.20	0.07	0.10	0.10
China	2007	Dy	1.60	0.00	0.00	0.07
China	2007	Gd	1.20	0.10	0.00	0.10
China	2007	Other Elements	1.50	0.00	0.00	0.08
China	2007	Tb	1.20	0.10	0.00	0.10
China	2007	Eu	1.50	0.00	0.00	0.08
China	2007	Sm	1.60	0.00	0.00	0.07
China	2006	Magnets	1.14	0.00	0.00	0.12
China	2006	Metallurgy Ex Batt	1.00	0.17	0.60	0.13
China	2006	Glass Additives	1.00	0.17	0.40	0.13
China	2006	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	2006	Polishing Powder	1.00	0.17	0.00	0.13
China	2006	Battery Alloys	1.00	0.17	0.00	0.13
China	2006	Phosphors	1.00	0.17	0.00	0.13
China	2006	Auto Catalysts	1.00	0.17	0.00	0.13
China	2006	Ce	1.10	0.16	0.40	0.10
China	2006	La	1.10	0.16	0.11	0.10
China	2006	Nd	1.10	0.20	0.39	0.10
China	2006	Pr	1.10	0.20	0.00	0.10
China	2006	Y	1.20	0.07	0.10	0.10
China	2006	Dy	1.60	0.00	0.00	0.07
China	2006	Gd	1.20	0.10	0.00	0.10
China	2006	Other Elements	1.50	0.00	0.00	0.08
China	2006	Tb	1.20	0.10	0.00	0.10
China	2006	Eu	1.50	0.00	0.00	0.08
China	2006	Sm	1.60	0.00	0.00	0.07
China	2005	Magnets	1.14	0.00	0.00	0.12
China	2005	Metallurgy Ex Batt	1.00	0.17	0.60	0.13
China	2005	Glass Additives	1.00	0.17	0.40	0.13
China	2005	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	2005	Polishing Powder	1.00	0.17	0.00	0.13
China	2005	Battery Alloys	1.00	0.17	0.00	0.13
China	2005	Phosphors	1.00	0.17	0.00	0.13

Country	Year	Element or Product	NSI	Betweenness	Weighted Betweenness	Closeness
China	2005	Auto Catalysts	1.00	0.17	0.00	0.13
China	2005	Ce	1.10	0.16	0.40	0.10
China	2005	La	1.10	0.16	0.11	0.10
China	2005	Nd	1.10	0.20	0.39	0.10
China	2005	Pr	1.10	0.20	0.00	0.10
China	2005	Y	1.20	0.07	0.10	0.10
China	2005	Dy	1.60	0.00	0.00	0.07
China	2005	Gd	1.20	0.10	0.00	0.10
China	2005	Other Elements	1.50	0.00	0.00	0.08
China	2005	Tb	1.20	0.10	0.00	0.10
China	2005	Sm	1.60	0.00	0.00	0.07
China	2005	Eu	1.50	0.00	0.00	0.08
China	2004	Magnets	1.14	0.00	0.00	0.12
China	2004	Glass Additives	1.00	0.17	0.60	0.13
China	2004	Metallurgy Ex Batt	1.00	0.17	0.40	0.13
China	2004	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	2004	Polishing Powder	1.00	0.17	0.00	0.13
China	2004	Battery Alloys	1.00	0.17	0.00	0.13
China	2004	Phosphors	1.00	0.17	0.00	0.13
China	2004	Auto Catalysts	1.00	0.17	0.00	0.13
China	2004	Ce	1.10	0.16	0.40	0.10
China	2004	La	1.10	0.16	0.11	0.10
China	2004	Nd	1.10	0.20	0.39	0.10
China	2004	Pr	1.10	0.20	0.00	0.10
China	2004	Y	1.20	0.07	0.10	0.10
China	2004	Dy	1.60	0.00	0.00	0.07
China	2004	Other Elements	1.50	0.00	0.00	0.08
China	2004	Gd	1.20	0.10	0.00	0.10
China	2004	Eu	1.50	0.00	0.00	0.08
China	2004	Tb	1.20	0.10	0.00	0.10
China	2004	Sm	1.60	0.00	0.00	0.07
China	2003	Glass Additives	1.00	0.17	0.60	0.13
China	2003	Metallurgy Ex Batt	1.00	0.17	0.40	0.13
China	2003	Magnets	1.14	0.00	0.00	0.12
China	2003	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	2003	Polishing Powder	1.00	0.17	0.00	0.13
China	2003	Battery Alloys	1.00	0.17	0.00	0.13
China	2003	Phosphors	1.00	0.17	0.00	0.13
China	2003	Auto Catalysts	1.00	0.17	0.00	0.13
China	2003	Ce	1.10	0.16	0.41	0.10
China	2003	La	1.10	0.16	0.11	0.10
China	2003	Nd	1.10	0.20	0.39	0.10
China	2003	Pr	1.10	0.20	0.00	0.10
China	2003	Y	1.20	0.07	0.09	0.10
China	2003	Dy	1.60	0.00	0.00	0.07
China	2003	Other Elements	1.50	0.00	0.00	0.08
China	2003	Gd	1.20	0.10	0.00	0.10
China	2003	Tb	1.20	0.10	0.00	0.10
China	2003	Sm	1.60	0.00	0.00	0.07
China	2003	Eu	1.50	0.00	0.00	0.08
China	2002	Metallurgy Ex Batt	1.00	0.17	0.60	0.13

Country	Year	Element or Product	NSI	Betweenness	Weighted Betweenness	Closeness
China	2002	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	2002	Magnets	1.14	0.00	0.00	0.12
China	2002	Glass Additives	1.00	0.17	0.40	0.13
China	2002	Polishing Powder	1.00	0.17	0.00	0.13
China	2002	Battery Alloys	1.00	0.17	0.00	0.13
China	2002	Phosphors	1.00	0.17	0.00	0.13
China	2002	Auto Catalysts	1.00	0.17	0.00	0.13
China	2002	La	1.10	0.16	0.11	0.10
China	2002	Ce	1.10	0.16	0.41	0.10
China	2002	Nd	1.10	0.20	0.39	0.10
China	2002	Pr	1.10	0.20	0.00	0.10
China	2002	Y	1.20	0.07	0.09	0.10
China	2002	Dy	1.60	0.00	0.00	0.07
China	2002	Other Elements	1.50	0.00	0.00	0.08
China	2002	Gd	1.20	0.10	0.00	0.10
China	2002	Eu	1.50	0.00	0.00	0.08
China	2002	Tb	1.20	0.10	0.00	0.10
China	2002	Sm	1.60	0.00	0.00	0.07
China	2001	Metallurgy Ex Batt	1.00	0.17	0.60	0.13
China	2001	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	2001	Magnets	1.14	0.00	0.00	0.12
China	2001	Glass Additives	1.00	0.17	0.40	0.13
China	2001	Polishing Powder	1.00	0.17	0.00	0.13
China	2001	Battery Alloys	1.00	0.17	0.00	0.13
China	2001	Phosphors	1.00	0.17	0.00	0.13
China	2001	Auto Catalysts	1.00	0.17	0.00	0.13
China	2001	La	1.10	0.16	0.11	0.10
China	2001	Ce	1.10	0.16	0.38	0.10
China	2001	Nd	1.10	0.20	0.38	0.10
China	2001	Pr	1.10	0.20	0.00	0.10
China	2001	Y	1.20	0.07	0.10	0.10
China	2001	Dy	1.60	0.00	0.00	0.07
China	2001	Other Elements	1.50	0.00	0.00	0.08
China	2001	Gd	1.20	0.10	0.04	0.10
China	2001	Eu	1.50	0.00	0.00	0.08
China	2001	Tb	1.20	0.10	0.00	0.10
China	2001	Sm	1.60	0.00	0.00	0.07
China	2000	Metallurgy Ex Batt	1.00	0.17	0.65	0.13
China	2000	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	2000	Magnets	1.14	0.00	0.00	0.12
China	2000	Glass Additives	1.00	0.17	0.35	0.13
China	2000	Polishing Powder	1.00	0.17	0.00	0.13
China	2000	Battery Alloys	1.00	0.17	0.00	0.13
China	2000	Phosphors	1.00	0.17	0.00	0.13
China	2000	Auto Catalysts	1.00	0.17	0.00	0.13
China	2000	La	1.10	0.19	0.09	0.10
China	2000	Ce	1.10	0.19	0.40	0.10
China	2000	Nd	1.20	0.16	0.34	0.10
China	2000	Pr	1.20	0.16	0.00	0.10
China	2000	Y	1.20	0.10	0.16	0.10
China	2000	Dy	1.70	0.00	0.00	0.07

Country	Year	Element or Product	NSI	Betweenness	Weighted Betweenness	Closeness
China	2000	Other Elements	1.50	0.00	0.00	0.08
China	2000	Gd	1.20	0.21	0.00	0.10
China	2000	Sm	1.60	0.00	0.00	0.08
China	2000	Eu	1.50	0.00	0.00	0.08
China	2000	Tb	1.50	0.00	0.00	0.08
China	1999	Metallurgy Ex Batt	1.00	0.17	0.68	0.13
China	1999	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	1999	Magnets	1.14	0.00	0.00	0.12
China	1999	Glass Additives	1.00	0.17	0.32	0.13
China	1999	Polishing Powder	1.00	0.17	0.00	0.13
China	1999	Battery Alloys	1.00	0.17	0.00	0.13
China	1999	Phosphors	1.00	0.17	0.00	0.13
China	1999	Auto Catalysts	1.00	0.17	0.00	0.13
China	1999	La	1.10	0.19	0.09	0.10
China	1999	Ce	1.10	0.19	0.40	0.10
China	1999	Nd	1.20	0.16	0.34	0.10
China	1999	Pr	1.20	0.16	0.00	0.10
China	1999	Y	1.20	0.10	0.16	0.10
China	1999	Dy	1.70	0.00	0.00	0.07
China	1999	Other Elements	1.50	0.00	0.00	0.08
China	1999	Gd	1.20	0.21	0.00	0.10
China	1999	Sm	1.60	0.00	0.00	0.08
China	1999	Eu	1.50	0.00	0.00	0.08
China	1999	Tb	1.50	0.00	0.00	0.08
China	1998	Metallurgy Ex Batt	1.00	0.25	0.70	0.13
China	1998	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	1998	Glass Additives	1.00	0.25	0.30	0.13
China	1998	Magnets	1.43	0.00	0.00	0.10
China	1998	Polishing Powder	1.00	0.25	0.00	0.13
China	1998	Battery Alloys	1.00	0.25	0.00	0.13
China	1998	Phosphors	1.14	0.00	0.00	0.12
China	1998	Auto Catalysts	1.14	0.00	0.00	0.12
China	1998	La	1.20	0.17	0.09	0.11
China	1998	Ce	1.20	0.17	0.41	0.11
China	1998	Nd	1.20	0.27	0.35	0.11
China	1998	Pr	1.20	0.27	0.00	0.11
China	1998	Y	1.30	0.12	0.15	0.10
China	1998	Dy	1.90	0.00	0.00	0.07
China	1998	Other Elements	1.50	0.00	0.00	0.09
China	1998	Gd	1.90	0.00	0.00	0.07
China	1998	Sm	1.60	0.00	0.00	0.08
China	1998	Eu	1.80	0.00	0.00	0.08
China	1998	Tb	1.80	0.00	0.00	0.08
China	1997	Metallurgy Ex Batt	1.00	0.25	0.73	0.13
China	1997	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	1997	Glass Additives	1.00	0.25	0.27	0.13
China	1997	Magnets	1.43	0.00	0.00	0.10
China	1997	Polishing Powder	1.00	0.25	0.00	0.13
China	1997	Battery Alloys	1.00	0.25	0.00	0.13
China	1997	Phosphors	1.14	0.00	0.00	0.12
China	1997	Auto Catalysts	1.14	0.00	0.00	0.12

Country	Year	Element or Product	NSI	Betweenness	Weighted Betweenness	Closeness
China	1997	La	1.20	0.17	0.09	0.11
China	1997	Ce	1.20	0.17	0.41	0.11
China	1997	Nd	1.20	0.27	0.35	0.11
China	1997	Pr	1.20	0.27	0.00	0.11
China	1997	Y	1.30	0.12	0.15	0.10
China	1997	Other Elements	1.50	0.00	0.00	0.09
China	1997	Dy	1.90	0.00	0.00	0.07
China	1997	Gd	1.90	0.00	0.00	0.07
China	1997	Sm	1.60	0.00	0.00	0.08
China	1997	Eu	1.80	0.00	0.00	0.08
China	1997	Tb	1.80	0.00	0.00	0.08
China	1996	Metallurgy Ex Batt	1.00	0.25	0.73	0.13
China	1996	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	1996	Glass Additives	1.00	0.25	0.27	0.13
China	1996	Magnets	1.43	0.00	0.00	0.10
China	1996	Polishing Powder	1.00	0.25	0.00	0.13
China	1996	Battery Alloys	1.00	0.25	0.00	0.13
China	1996	Phosphors	1.14	0.00	0.00	0.12
China	1996	Auto Catalysts	1.14	0.00	0.00	0.12
China	1996	La	1.20	0.17	0.09	0.11
China	1996	Ce	1.20	0.17	0.41	0.11
China	1996	Nd	1.20	0.27	0.35	0.11
China	1996	Pr	1.20	0.27	0.00	0.11
China	1996	Y	1.30	0.12	0.15	0.10
China	1996	Other Elements	1.50	0.00	0.00	0.09
China	1996	Dy	1.90	0.00	0.00	0.07
China	1996	Sm	1.60	0.00	0.00	0.08
China	1996	Eu	1.80	0.00	0.00	0.08
China	1996	Gd	1.90	0.00	0.00	0.07
China	1996	Tb	1.80	0.00	0.00	0.08
China	1995	Metallurgy Ex Batt	1.00	0.25	0.77	0.13
China	1995	Fuel Cracking Catalysts	1.14	0.00	0.00	0.12
China	1995	Glass Additives	1.00	0.25	0.23	0.13
China	1995	Magnets	1.43	0.00	0.00	0.10
China	1995	Polishing Powder	1.00	0.25	0.00	0.13
China	1995	Battery Alloys	1.00	0.25	0.00	0.13
China	1995	Phosphors	1.14	0.00	0.00	0.12
China	1995	Auto Catalysts	1.14	0.00	0.00	0.12
China	1995	La	1.29	0.00	0.00	0.13
China	1995	Ce	1.29	0.00	0.51	0.13
China	1995	Nd	1.00	0.50	0.49	0.15
China	1995	Pr	1.00	0.50	0.00	0.15
China	1995	Y	1.29	0.00	0.00	0.13
China	1995	Other Elements	1.29	0.00	0.00	0.13
China	1995	Dy	1.57	0.00	0.00	0.10
China	1995	Gd	1.57	0.00	0.00	0.10

Country	Year	Element or Product	Weighted Closeness	Fisher Alpha	Partner Diversity	Effective Partners
China	2007	Magnets	0.23	NA	0.83	2.30
China	2007	Metallurgy Ex Batt	0.16	NA	1.15	3.15
China	2007	Glass Additives	0.12	NA	0.97	2.65
China	2007	Fuel Cracking Catalysts	0.13	NA	0.33	1.39
China	2007	Polishing Powder	0.11	NA	0.76	2.14
China	2007	Battery Alloys	0.09	NA	1.17	3.21
China	2007	Phosphors	0.05	NA	1.07	2.91
China	2007	Auto Catalysts	0.05	NA	0.42	1.52
China	2007	Ce	0.18	NA	1.69	5.41
China	2007	La	0.15	NA	1.58	4.84
China	2007	Nd	0.09	NA	0.58	1.79
China	2007	Pr	0.06	NA	0.75	2.11
China	2007	Y	0.08	NA	0.21	1.23
China	2007	Dy	0.03	NA	0.00	1.00
China	2007	Gd	0.01	NA	0.42	1.53
China	2007	Other Elements	0.01	NA	0.00	1.00
China	2007	Tb	0.01	NA	0.45	1.57
China	2007	Eu	0.01	NA	0.00	1.00
China	2007	Sm	0.01	NA	0.00	1.00
China	2006	Magnets	0.23	NA	0.83	2.30
China	2006	Metallurgy Ex Batt	0.17	NA	1.15	3.14
China	2006	Glass Additives	0.14	NA	0.98	2.66
China	2006	Fuel Cracking Catalysts	0.13	NA	0.32	1.38
China	2006	Polishing Powder	0.11	NA	0.76	2.15
China	2006	Battery Alloys	0.09	NA	1.17	3.21
China	2006	Phosphors	0.05	NA	1.07	2.92
China	2006	Auto Catalysts	0.05	NA	0.42	1.52
China	2006	Ce	0.18	NA	1.66	5.26
China	2006	La	0.15	NA	1.56	4.76
China	2006	Nd	0.10	NA	0.62	1.86
China	2006	Pr	0.07	NA	0.77	2.17
China	2006	Y	0.08	NA	0.24	1.28
China	2006	Dy	0.03	NA	0.00	1.00
China	2006	Gd	0.01	NA	0.43	1.54
China	2006	Other Elements	0.01	NA	0.00	1.00
China	2006	Tb	0.01	NA	0.50	1.65
China	2006	Eu	0.01	NA	0.00	1.00
China	2006	Sm	0.01	NA	0.00	1.00
China	2005	Magnets	0.23	NA	0.83	2.30
China	2005	Metallurgy Ex Batt	0.20	NA	1.15	3.15
China	2005	Glass Additives	0.14	NA	0.98	2.66
China	2005	Fuel Cracking Catalysts	0.14	NA	0.32	1.38
China	2005	Polishing Powder	0.11	NA	0.76	2.15
China	2005	Battery Alloys	0.09	NA	1.17	3.23
China	2005	Phosphors	0.05	NA	1.07	2.92

Country	Year	Element or Product	Weighted Closeness	Fisher Alpha	Partner Diversity	Effective Partners
China	2005	Auto Catalysts	0.04	NA	0.45	1.57
China	2005	Ce	0.18	NA	1.63	5.11
China	2005	La	0.15	NA	1.54	4.69
China	2005	Nd	0.10	NA	0.66	1.94
China	2005	Pr	0.07	NA	0.82	2.27
China	2005	Y	0.07	NA	0.25	1.29
China	2005	Dy	0.02	NA	0.00	1.00
China	2005	Gd	0.01	NA	0.43	1.54
China	2005	Other Elements	0.01	NA	0.00	1.00
China	2005	Tb	0.01	NA	0.45	1.57
China	2005	Sm	0.01	NA	0.00	1.00
China	2005	Eu	0.01	NA	0.00	1.00
China	2004	Magnets	0.24	NA	0.83	2.29
China	2004	Glass Additives	0.16	NA	0.97	2.65
China	2004	Metallurgy Ex Batt	0.15	NA	1.15	3.15
China	2004	Fuel Cracking Catalysts	0.13	NA	0.32	1.38
China	2004	Polishing Powder	0.10	NA	0.76	2.14
China	2004	Battery Alloys	0.08	NA	1.16	3.20
China	2004	Phosphors	0.05	NA	1.07	2.90
China	2004	Auto Catalysts	0.04	NA	0.45	1.57
China	2004	Ce	0.19	NA	1.59	4.92
China	2004	La	0.15	NA	1.55	4.69
China	2004	Nd	0.09	NA	0.65	1.91
China	2004	Pr	0.06	NA	0.79	2.21
China	2004	Y	0.07	NA	0.34	1.40
China	2004	Dy	0.02	NA	0.00	1.00
China	2004	Other Elements	0.02	NA	0.00	1.00
China	2004	Gd	0.01	NA	0.38	1.46
China	2004	Eu	0.01	NA	0.00	1.00
China	2004	Tb	0.01	NA	0.41	1.51
China	2004	Sm	0.00	NA	0.00	1.00
China	2003	Glass Additives	0.19	NA	0.97	2.64
China	2003	Metallurgy Ex Batt	0.19	NA	1.14	3.14
China	2003	Magnets	0.20	NA	0.83	2.30
China	2003	Fuel Cracking Catalysts	0.17	NA	0.32	1.38
China	2003	Polishing Powder	0.08	NA	0.76	2.14
China	2003	Battery Alloys	0.06	NA	1.17	3.22
China	2003	Phosphors	0.04	NA	1.07	2.92
China	2003	Auto Catalysts	0.03	NA	0.46	1.59
China	2003	Ce	0.17	NA	1.49	4.45
China	2003	La	0.15	NA	1.38	3.97
China	2003	Nd	0.09	NA	0.78	2.18
China	2003	Pr	0.06	NA	0.91	2.48
China	2003	Y	0.06	NA	0.41	1.51
China	2003	Dy	0.02	NA	0.00	1.00
China	2003	Other Elements	0.02	NA	0.00	1.00
China	2003	Gd	0.01	NA	0.47	1.61
China	2003	Tb	0.00	NA	0.50	1.65
China	2003	Sm	0.00	NA	0.00	1.00
China	2003	Eu	0.00	NA	0.00	1.00
China	2002	Metallurgy Ex Batt	0.26	NA	1.15	3.14

Country	Year	Element or Product	Weighted Closeness	Fisher Alpha	Partner Diversity	Effective Partners
China	2002	Fuel Cracking Catalysts	0.23	NA	0.33	1.39
China	2002	Magnets	0.17	NA	0.84	2.31
China	2002	Glass Additives	0.15	NA	0.97	2.65
China	2002	Polishing Powder	0.07	NA	0.76	2.14
China	2002	Battery Alloys	0.05	NA	1.14	3.13
China	2002	Phosphors	0.03	NA	1.07	2.91
China	2002	Auto Catalysts	0.03	NA	0.50	1.64
China	2002	La	0.14	NA	1.23	3.42
China	2002	Ce	0.15	NA	1.48	4.40
China	2002	Nd	0.10	NA	0.83	2.29
China	2002	Pr	0.06	NA	0.95	2.58
China	2002	Y	0.05	NA	0.37	1.45
China	2002	Dy	0.02	NA	0.00	1.00
China	2002	Other Elements	0.01	NA	0.00	1.00
China	2002	Gd	0.01	NA	0.45	1.57
China	2002	Eu	0.00	NA	0.00	1.00
China	2002	Tb	0.00	NA	0.64	1.89
China	2002	Sm	0.00	NA	0.00	1.00
China	2001	Metallurgy Ex Batt	0.26	NA	1.15	3.15
China	2001	Fuel Cracking Catalysts	0.22	NA	0.33	1.39
China	2001	Magnets	0.18	NA	0.85	2.33
China	2001	Glass Additives	0.15	NA	0.96	2.62
China	2001	Polishing Powder	0.07	NA	0.75	2.13
China	2001	Battery Alloys	0.06	NA	1.14	3.14
China	2001	Phosphors	0.03	NA	1.08	2.94
China	2001	Auto Catalysts	0.03	NA	0.48	1.62
China	2001	La	0.14	NA	1.25	3.49
China	2001	Ce	0.15	NA	1.48	4.41
China	2001	Nd	0.10	NA	0.83	2.29
China	2001	Pr	0.06	NA	0.93	2.54
China	2001	Y	0.05	NA	0.37	1.44
China	2001	Dy	0.02	NA	0.00	1.00
China	2001	Other Elements	0.01	NA	0.00	1.00
China	2001	Gd	0.01	NA	0.41	1.51
China	2001	Eu	0.00	NA	0.00	1.00
China	2001	Tb	0.00	NA	0.64	1.89
China	2001	Sm	0.00	NA	0.00	1.00
China	2000	Metallurgy Ex Batt	0.29	NA	1.15	3.14
China	2000	Fuel Cracking Catalysts	0.25	NA	0.33	1.39
China	2000	Magnets	0.16	NA	0.82	2.26
China	2000	Glass Additives	0.14	NA	0.97	2.65
China	2000	Polishing Powder	0.06	NA	0.74	2.11
China	2000	Battery Alloys	0.05	NA	1.19	3.28
China	2000	Phosphors	0.03	NA	1.08	2.96
China	2000	Auto Catalysts	0.02	NA	0.34	1.41
China	2000	La	0.10	NA	1.15	3.15
China	2000	Ce	0.11	NA	1.42	4.15
China	2000	Nd	0.08	NA	0.86	2.36
China	2000	Pr	0.05	NA	0.94	2.57
China	2000	Y	0.05	NA	0.33	1.38
China	2000	Dy	0.02	NA	0.00	1.00

Country	Year	Element or Product	Weighted Closeness	Fisher Alpha	Partner Diversity	Effective Partners
China	2000	Other Elements	0.01	NA	0.00	1.00
China	2000	Gd	0.01	NA	0.50	1.65
China	2000	Sm	0.00	NA	0.00	1.00
China	2000	Eu	0.00	NA	0.00	1.00
China	2000	Tb	0.00	NA	0.00	1.00
China	1999	Metallurgy Ex Batt	0.31	NA	1.15	3.15
China	1999	Fuel Cracking Catalysts	0.27	NA	0.33	1.38
China	1999	Magnets	0.14	NA	0.82	2.27
China	1999	Glass Additives	0.14	NA	0.99	2.68
China	1999	Polishing Powder	0.05	NA	0.77	2.16
China	1999	Battery Alloys	0.04	NA	1.12	3.06
China	1999	Phosphors	0.03	NA	1.05	2.86
China	1999	Auto Catalysts	0.02	NA	0.41	1.51
China	1999	La	0.09	NA	1.09	2.99
China	1999	Ce	0.10	NA	1.36	3.88
China	1999	Nd	0.07	NA	0.89	2.44
China	1999	Pr	0.05	NA	0.97	2.63
China	1999	Y	0.04	NA	0.38	1.46
China	1999	Dy	0.01	NA	0.00	1.00
China	1999	Other Elements	0.01	NA	0.00	1.00
China	1999	Gd	0.01	NA	0.56	1.75
China	1999	Sm	0.00	NA	0.00	1.00
China	1999	Eu	0.00	NA	0.00	1.00
China	1999	Tb	0.00	NA	0.00	1.00
China	1998	Metallurgy Ex Batt	0.31	NA	1.15	3.15
China	1998	Fuel Cracking Catalysts	0.26	NA	0.32	1.38
China	1998	Glass Additives	0.13	NA	0.97	2.64
China	1998	Magnets	0.11	NA	0.83	2.29
China	1998	Polishing Powder	0.04	NA	0.73	2.07
China	1998	Battery Alloys	0.03	NA	1.14	3.12
China	1998	Phosphors	0.02	NA	0.98	2.65
China	1998	Auto Catalysts	0.02	NA	0.24	1.28
China	1998	La	0.07	NA	1.06	2.89
China	1998	Ce	0.08	NA	1.30	3.68
China	1998	Nd	0.06	NA	0.86	2.37
China	1998	Pr	0.04	NA	0.92	2.51
China	1998	Y	0.03	NA	0.42	1.53
China	1998	Dy	0.01	NA	0.00	1.00
China	1998	Other Elements	0.01	NA	0.00	1.00
China	1998	Gd	0.01	NA	0.00	1.00
China	1998	Sm	0.00	NA	0.00	1.00
China	1998	Eu	0.00	NA	0.00	1.00
China	1998	Tb	0.00	NA	0.00	1.00
China	1997	Metallurgy Ex Batt	0.34	NA	1.15	3.14
China	1997	Fuel Cracking Catalysts	0.26	NA	0.33	1.39
China	1997	Glass Additives	0.14	NA	0.97	2.64
China	1997	Magnets	0.09	NA	0.83	2.29
China	1997	Polishing Powder	0.03	NA	0.77	2.15
China	1997	Battery Alloys	0.03	NA	1.21	3.35
China	1997	Phosphors	0.02	NA	1.04	2.82
China	1997	Auto Catalysts	0.01	NA	0.00	1.00

Country	Year	Element or Product	Weighted Closeness	Fisher Alpha	Partner Diversity	Effective Partners
China	1997	La	0.06	NA	1.00	2.71
China	1997	Ce	0.06	NA	1.19	3.30
China	1997	Nd	0.05	NA	0.87	2.39
China	1997	Pr	0.03	NA	0.96	2.61
China	1997	Y	0.03	NA	0.52	1.68
China	1997	Other Elements	0.01	NA	0.00	1.00
China	1997	Dy	0.01	NA	0.00	1.00
China	1997	Gd	0.00	NA	0.00	1.00
China	1997	Sm	0.00	NA	0.00	1.00
China	1997	Eu	0.00	NA	0.00	1.00
China	1997	Tb	0.00	NA	0.00	1.00
China	1996	Metallurgy Ex Batt	0.36	NA	1.15	3.15
China	1996	Fuel Cracking Catalysts	0.27	NA	0.33	1.38
China	1996	Glass Additives	0.13	NA	0.97	2.64
China	1996	Magnets	0.09	NA	0.82	2.27
China	1996	Polishing Powder	0.03	NA	0.78	2.18
China	1996	Battery Alloys	0.03	NA	1.24	3.45
China	1996	Phosphors	0.02	NA	1.13	3.09
China	1996	Auto Catalysts	0.01	NA	0.00	1.00
China	1996	La	0.05	NA	0.99	2.69
China	1996	Ce	0.06	NA	1.15	3.17
China	1996	Nd	0.05	NA	0.87	2.38
China	1996	Pr	0.03	NA	0.96	2.62
China	1996	Y	0.02	NA	0.47	1.61
China	1996	Other Elements	0.01	NA	0.00	1.00
China	1996	Dy	0.01	NA	0.00	1.00
China	1996	Sm	0.00	NA	0.00	1.00
China	1996	Eu	0.00	NA	0.00	1.00
China	1996	Gd	0.00	NA	0.00	1.00
China	1996	Tb	0.00	NA	0.00	1.00
China	1995	Metallurgy Ex Batt	0.36	NA	1.15	3.15
China	1995	Fuel Cracking Catalysts	0.28	NA	0.32	1.38
China	1995	Glass Additives	0.14	NA	0.95	2.59
China	1995	Magnets	0.07	NA	0.84	2.32
China	1995	Polishing Powder	0.03	NA	0.81	2.24
China	1995	Battery Alloys	0.02	NA	0.90	2.46
China	1995	Phosphors	0.01	NA	0.68	1.98
China	1995	Auto Catalysts	0.01	NA	0.00	1.00
China	1995	La	0.16	NA	0.97	2.63
China	1995	Ce	0.18	NA	1.11	3.02
China	1995	Nd	0.12	NA	0.81	2.26
China	1995	Pr	0.05	NA	0.88	2.40
China	1995	Y	0.02	NA	0.53	1.70
China	1995	Other Elements	0.01	NA	0.00	1.00
China	1995	Dy	0.01	NA	0.00	1.00
China	1995	Gd	0.00	NA	0.00	1.00

Country	Year	Element or Product	Proportional Generality	Proportional Similarity	d
China	2007	Magnets	0.47	0.37	0.84
China	2007	Metallurgy Ex Batt	0.64	0.79	0.05
China	2007	Glass Additives	0.54	0.62	0.16
China	2007	Fuel Cracking Catalysts	0.28	0.36	0.43
China	2007	Polishing Powder	0.44	0.61	0.16
China	2007	Battery Alloys	0.65	0.71	0.05
China	2007	Phosphors	0.59	0.25	0.68
China	2007	Auto Catalysts	0.31	0.41	0.08
China	2007	Ce	0.81	0.57	0.46
China	2007	La	0.72	0.61	0.43
China	2007	Nd	0.27	0.47	0.52
China	2007	Pr	0.31	0.51	0.10
China	2007	Y	0.18	0.11	0.76
China	2007	Dy	0.15	0.31	0.00
China	2007	Gd	0.23	0.37	0.00
China	2007	Other Elements	0.15	0.12	0.22
China	2007	Tb	0.23	0.23	0.20
China	2007	Eu	0.15	0.06	0.35
China	2007	Sm	0.15	0.08	0.28
China	2006	Magnets	0.47	0.35	0.83
China	2006	Metallurgy Ex Batt	0.65	0.80	0.04
China	2006	Glass Additives	0.55	0.63	0.16
China	2006	Fuel Cracking Catalysts	0.29	0.37	0.42
China	2006	Polishing Powder	0.44	0.63	0.13
China	2006	Battery Alloys	0.66	0.73	0.04
China	2006	Phosphors	0.60	0.25	0.63
China	2006	Auto Catalysts	0.31	0.42	0.00
China	2006	Ce	0.78	0.59	0.44
China	2006	La	0.71	0.62	0.41
China	2006	Nd	0.28	0.47	0.50
China	2006	Pr	0.32	0.50	0.13
China	2006	Y	0.19	0.12	0.69
China	2006	Dy	0.15	0.29	0.00
China	2006	Gd	0.23	0.35	0.00
China	2006	Other Elements	0.15	0.14	0.19
China	2006	Tb	0.25	0.26	0.18
China	2006	Eu	0.15	0.06	0.35
China	2006	Sm	0.15	0.08	0.28
China	2005	Magnets	0.48	0.34	0.82
China	2005	Metallurgy Ex Batt	0.66	0.81	0.03
China	2005	Glass Additives	0.56	0.64	0.14
China	2005	Fuel Cracking Catalysts	0.29	0.37	0.42
China	2005	Polishing Powder	0.45	0.64	0.12
China	2005	Battery Alloys	0.68	0.74	0.00
China	2005	Phosphors	0.61	0.25	0.64

Country	Year	Element or Product	Proportional Generality	Proportional Similarity	d
China	2005	Auto Catalysts	0.33	0.44	0.00
China	2005	Ce	0.77	0.60	0.41
China	2005	La	0.70	0.63	0.38
China	2005	Nd	0.29	0.47	0.48
China	2005	Pr	0.34	0.51	0.06
China	2005	Y	0.19	0.12	0.68
China	2005	Dy	0.15	0.27	0.00
China	2005	Gd	0.23	0.33	0.00
China	2005	Other Elements	0.15	0.14	0.17
China	2005	Tb	0.24	0.22	0.20
China	2005	Sm	0.15	0.07	0.28
China	2005	Eu	0.15	0.05	0.35
China	2004	Magnets	0.48	0.33	0.83
China	2004	Glass Additives	0.56	0.65	0.15
China	2004	Metallurgy Ex Batt	0.66	0.82	0.00
China	2004	Fuel Cracking Catalysts	0.29	0.37	0.41
China	2004	Polishing Powder	0.45	0.65	0.00
China	2004	Battery Alloys	0.67	0.75	0.00
China	2004	Phosphors	0.61	0.25	0.51
China	2004	Auto Catalysts	0.33	0.45	0.00
China	2004	Ce	0.74	0.60	0.39
China	2004	La	0.70	0.64	0.34
China	2004	Nd	0.29	0.45	0.47
China	2004	Pr	0.33	0.48	0.00
China	2004	Y	0.21	0.16	0.61
China	2004	Dy	0.15	0.27	0.00
China	2004	Other Elements	0.15	0.20	0.08
China	2004	Gd	0.22	0.32	0.00
China	2004	Eu	0.15	0.05	0.36
China	2004	Tb	0.23	0.19	0.22
China	2004	Sm	0.15	0.07	0.28
China	2003	Glass Additives	0.60	0.67	0.12
China	2003	Metallurgy Ex Batt	0.72	0.84	0.00
China	2003	Magnets	0.52	0.27	0.80
China	2003	Fuel Cracking Catalysts	0.31	0.43	0.41
China	2003	Polishing Powder	0.49	0.71	0.00
China	2003	Battery Alloys	0.73	0.80	0.00
China	2003	Phosphors	0.67	0.23	0.55
China	2003	Auto Catalysts	0.36	0.47	0.00
China	2003	Ce	0.70	0.63	0.28
China	2003	La	0.63	0.65	0.28
China	2003	Nd	0.34	0.45	0.45
China	2003	Pr	0.39	0.48	0.00
China	2003	Y	0.24	0.18	0.56
China	2003	Dy	0.16	0.20	0.05
China	2003	Other Elements	0.16	0.23	0.00
China	2003	Gd	0.25	0.24	0.00
China	2003	Tb	0.26	0.24	0.21
China	2003	Sm	0.16	0.05	0.30
China	2003	Eu	0.16	0.04	0.37
China	2002	Metallurgy Ex Batt	0.76	0.83	0.00

Country	Year	Element or Product	Proportional Generality	Proportional Similarity	d
China	2002	Fuel Cracking Catalysts	0.33	0.47	0.40
China	2002	Magnets	0.55	0.25	0.74
China	2002	Glass Additives	0.64	0.65	0.00
China	2002	Polishing Powder	0.52	0.70	0.00
China	2002	Battery Alloys	0.75	0.84	0.00
China	2002	Phosphors	0.70	0.23	0.57
China	2002	Auto Catalysts	0.40	0.47	0.00
China	2002	La	0.58	0.64	0.26
China	2002	Ce	0.75	0.64	0.21
China	2002	Nd	0.39	0.50	0.19
China	2002	Pr	0.44	0.51	0.00
China	2002	Y	0.25	0.15	0.67
China	2002	Dy	0.17	0.17	0.15
China	2002	Other Elements	0.17	0.15	0.17
China	2002	Gd	0.27	0.20	0.09
China	2002	Eu	0.17	0.03	0.43
China	2002	Tb	0.32	0.20	0.20
China	2002	Sm	0.17	0.04	0.34
China	2001	Metallurgy Ex Batt	0.75	0.83	0.00
China	2001	Fuel Cracking Catalysts	0.33	0.47	0.40
China	2001	Magnets	0.56	0.25	0.74
China	2001	Glass Additives	0.63	0.65	0.00
China	2001	Polishing Powder	0.51	0.69	0.00
China	2001	Battery Alloys	0.75	0.84	0.00
China	2001	Phosphors	0.70	0.24	0.55
China	2001	Auto Catalysts	0.39	0.46	0.00
China	2001	La	0.59	0.64	0.27
China	2001	Ce	0.74	0.64	0.22
China	2001	Nd	0.39	0.50	0.17
China	2001	Pr	0.43	0.51	0.00
China	2001	Y	0.24	0.15	0.67
China	2001	Dy	0.17	0.17	0.15
China	2001	Other Elements	0.17	0.15	0.17
China	2001	Gd	0.25	0.20	0.08
China	2001	Eu	0.17	0.03	0.43
China	2001	Tb	0.32	0.20	0.19
China	2001	Sm	0.17	0.05	0.34
China	2000	Metallurgy Ex Batt	0.78	0.82	0.00
China	2000	Fuel Cracking Catalysts	0.35	0.49	0.39
China	2000	Magnets	0.56	0.23	0.72
China	2000	Glass Additives	0.66	0.64	0.00
China	2000	Polishing Powder	0.52	0.68	0.00
China	2000	Battery Alloys	0.82	0.86	0.00
China	2000	Phosphors	0.74	0.21	0.62
China	2000	Auto Catalysts	0.35	0.42	0.00
China	2000	La	0.57	0.65	0.25
China	2000	Ce	0.75	0.64	0.17
China	2000	Nd	0.43	0.52	0.25
China	2000	Pr	0.46	0.53	0.00
China	2000	Y	0.25	0.13	0.73
China	2000	Dy	0.18	0.15	0.20

Country	Year	Element or Product	Proportional Generality	Proportional Similarity	d
China	2000	Other Elements	0.18	0.12	0.23
China	2000	Gd	0.30	0.18	0.13
China	2000	Sm	0.18	0.04	0.38
China	2000	Eu	0.18	0.03	0.45
China	2000	Tb	0.18	0.03	0.45
China	1999	Metallurgy Ex Batt	0.82	0.81	0.00
China	1999	Fuel Cracking Catalysts	0.36	0.51	0.38
China	1999	Magnets	0.59	0.22	0.55
China	1999	Glass Additives	0.70	0.65	0.00
China	1999	Polishing Powder	0.56	0.70	0.00
China	1999	Battery Alloys	0.80	0.88	0.00
China	1999	Phosphors	0.75	0.22	0.60
China	1999	Auto Catalysts	0.39	0.45	0.00
China	1999	La	0.58	0.65	0.23
China	1999	Ce	0.75	0.65	0.13
China	1999	Nd	0.47	0.53	0.00
China	1999	Pr	0.51	0.55	0.00
China	1999	Y	0.28	0.15	0.72
China	1999	Dy	0.19	0.13	0.26
China	1999	Other Elements	0.19	0.12	0.24
China	1999	Gd	0.34	0.15	0.19
China	1999	Sm	0.19	0.03	0.39
China	1999	Eu	0.19	0.02	0.44
China	1999	Tb	0.19	0.02	0.44
China	1998	Metallurgy Ex Batt	0.84	0.80	0.00
China	1998	Fuel Cracking Catalysts	0.37	0.52	0.36
China	1998	Glass Additives	0.71	0.65	0.00
China	1998	Magnets	0.61	0.20	0.56
China	1998	Polishing Powder	0.56	0.69	0.00
China	1998	Battery Alloys	0.84	0.88	0.00
China	1998	Phosphors	0.71	0.23	0.61
China	1998	Auto Catalysts	0.34	0.42	0.00
China	1998	La	0.59	0.66	0.12
China	1998	Ce	0.75	0.66	0.09
China	1998	Nd	0.49	0.53	0.00
China	1998	Pr	0.51	0.54	0.00
China	1998	Y	0.31	0.14	0.72
China	1998	Dy	0.21	0.11	0.29
China	1998	Other Elements	0.21	0.12	0.26
China	1998	Gd	0.21	0.11	0.25
China	1998	Sm	0.21	0.03	0.42
China	1998	Eu	0.21	0.02	0.48
China	1998	Tb	0.21	0.02	0.48
China	1997	Metallurgy Ex Batt	0.88	0.80	0.00
China	1997	Fuel Cracking Catalysts	0.39	0.54	0.33
China	1997	Glass Additives	0.74	0.66	0.00
China	1997	Magnets	0.64	0.18	0.54
China	1997	Polishing Powder	0.60	0.71	0.00
China	1997	Battery Alloys	0.94	0.89	0.00
China	1997	Phosphors	0.79	0.20	0.64
China	1997	Auto Catalysts	0.28	0.36	0.05

Country	Year	Element or Product	Proportional Generality	Proportional Similarity	d
China	1997	La	0.62	0.67	0.12
China	1997	Ce	0.75	0.68	0.01
China	1997	Nd	0.55	0.54	0.00
China	1997	Pr	0.60	0.56	0.00
China	1997	Y	0.38	0.14	0.68
China	1997	Other Elements	0.23	0.13	0.26
China	1997	Dy	0.23	0.08	0.35
China	1997	Gd	0.23	0.08	0.31
China	1997	Sm	0.23	0.02	0.49
China	1997	Eu	0.23	0.02	0.54
China	1997	Tb	0.23	0.02	0.54
China	1996	Metallurgy Ex Batt	0.89	0.80	0.00
China	1996	Fuel Cracking Catalysts	0.39	0.54	0.33
China	1996	Glass Additives	0.75	0.67	0.00
China	1996	Magnets	0.65	0.18	0.52
China	1996	Polishing Powder	0.62	0.72	0.00
China	1996	Battery Alloys	0.98	0.88	0.00
China	1996	Phosphors	0.88	0.23	0.62
China	1996	Auto Catalysts	0.28	0.37	0.04
China	1996	La	0.64	0.67	0.12
China	1996	Ce	0.75	0.69	0.00
China	1996	Nd	0.56	0.55	0.00
China	1996	Pr	0.62	0.57	0.00
China	1996	Y	0.38	0.14	0.70
China	1996	Other Elements	0.24	0.12	0.28
China	1996	Dy	0.24	0.07	0.38
China	1996	Sm	0.24	0.02	0.50
China	1996	Eu	0.24	0.01	0.56
China	1996	Gd	0.24	0.07	0.30
China	1996	Tb	0.24	0.01	0.56
China	1995	Metallurgy Ex Batt	0.94	0.79	0.00
China	1995	Fuel Cracking Catalysts	0.41	0.55	0.31
China	1995	Glass Additives	0.77	0.67	0.00
China	1995	Magnets	0.69	0.16	0.51
China	1995	Polishing Powder	0.67	0.71	0.00
China	1995	Battery Alloys	0.73	0.90	0.00
China	1995	Phosphors	0.59	0.23	0.60
China	1995	Auto Catalysts	0.30	0.37	0.04
China	1995	La	0.66	0.68	0.03
China	1995	Ce	0.77	0.70	0.02
China	1995	Nd	0.57	0.54	0.00
China	1995	Pr	0.61	0.55	0.00
China	1995	Y	0.43	0.14	0.71
China	1995	Other Elements	0.25	0.13	0.27
China	1995	Dy	0.25	0.06	0.42
China	1995	Gd	0.25	0.06	0.34

APPENDIX C. Full-Size Graphical Results

R was used to generate the results figures shown. Each figure utilizes the common code shown here to load and manipulate the tidy data tables in Appendix B.

```
# load packages; ggplot
library(ggplot2)

# set working directory
setwd("")

# read in Group data
file <- read.csv("Group_Bipartite Results_for R.csv")

# check data
head(file, n=3)

# rename data
group_results <- file

# read in Species data
file <- read.csv("Species_Bipartite Results_for R.csv")

# check data
head(file, n=3)

# rename data
species_results <- file

file <- read.csv("Network_Bipartite Results_for R.csv")

head(file, n=3)

network_results <- file

# remove "file"
rm(file)

# Need to tag elements and products in the species data file.

# Products = Magnets, Metallurgy Ex Batt, Glass Additives, Fuel Cracking Catalysts,
# Polishing Powder, Battery Alloys, Phosphors, Auto Catalysts, Other Uses, Electronics,
# Ceramics

# Elements = La, Ce, Pr, Nd, Sm, Eu, Gd, Tb, Dy, Y, Other Elements
```

```
# Product
species_results$Elem.or.Prod[!is.na(match(species_results$Element.or.Product, c("Magnets", "Metallurgy Ex Batt", "Glass Additives", "Fuel Cracking Catalysts", "Polishing Powder", "Battery Alloys", "Phosphors", "Auto Catalysts", "Other Uses", "Electronics", "Ceramics")))] <- "Product"

# Element
species_results$Elem.or.Prod[!is.na(match(species_results$Element.or.Product, c("La", "Ce", "Pr", "Nd", "Sm", "Eu", "Gd", "Tb", "Dy", "Y", "Other Elements")))] <- "Element"

# split data based on element or product
element_species <- species_results[species_results$Elem.or.Prod == 'Element',]

product_species <- species_results[species_results$Elem.or.Prod == 'Product',]

# ensure years match data years
element_species2 <- element_species[ which(element_species$Year <= 2007), ]
product_species2 <- product_species[ which(product_species$Year <= 2007), ]
```

C-1. Partner Diversity

The following R code, combined with the above, will produce the following Partner Diversity figures.

```
# Portrait
g <- ggplot(element_species2, aes(x=Year, y=Partner.Diversity, fill=Element.or.Product)) +
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("Partner Diversity for Individual Elements") +
    facet_grid(facets=Element.or.Product ~ Country) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(colour="black"))
g
```

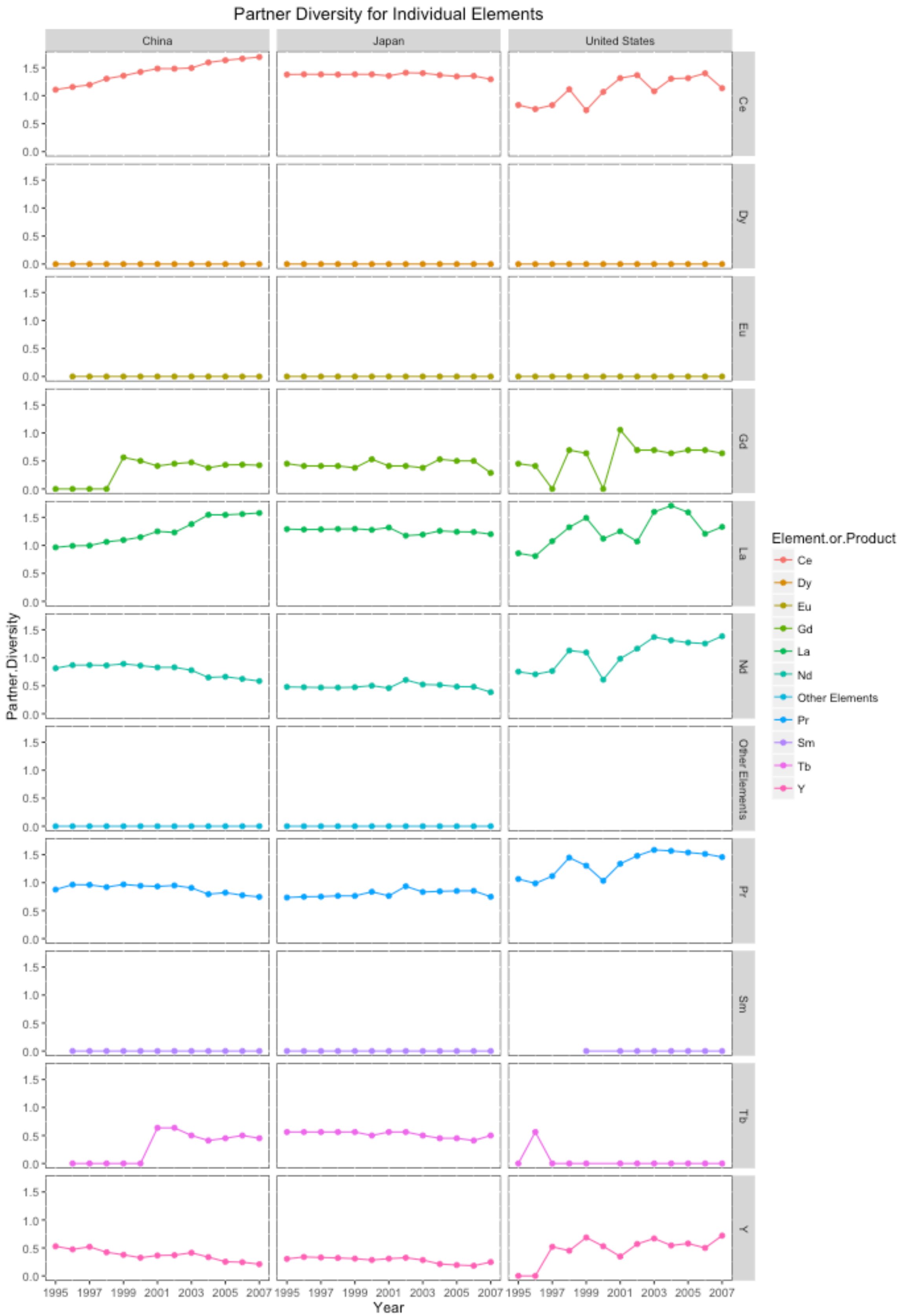

Figure 38. Partner Diversity Figure in Portrait Orientation

```
# Landscape
g <- ggplot(element_species2, aes(x=Year, y=Partner.Diversity, fill=Element.or.Product)) +
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("Partner Diversity for Individual Elements") +
    facet_grid(facets=Country ~ Element.or.Product) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(color="black")) +
    theme(panel.grid = element_blank()) +
    theme_bw() +
    theme(legend.position="none")
g
```

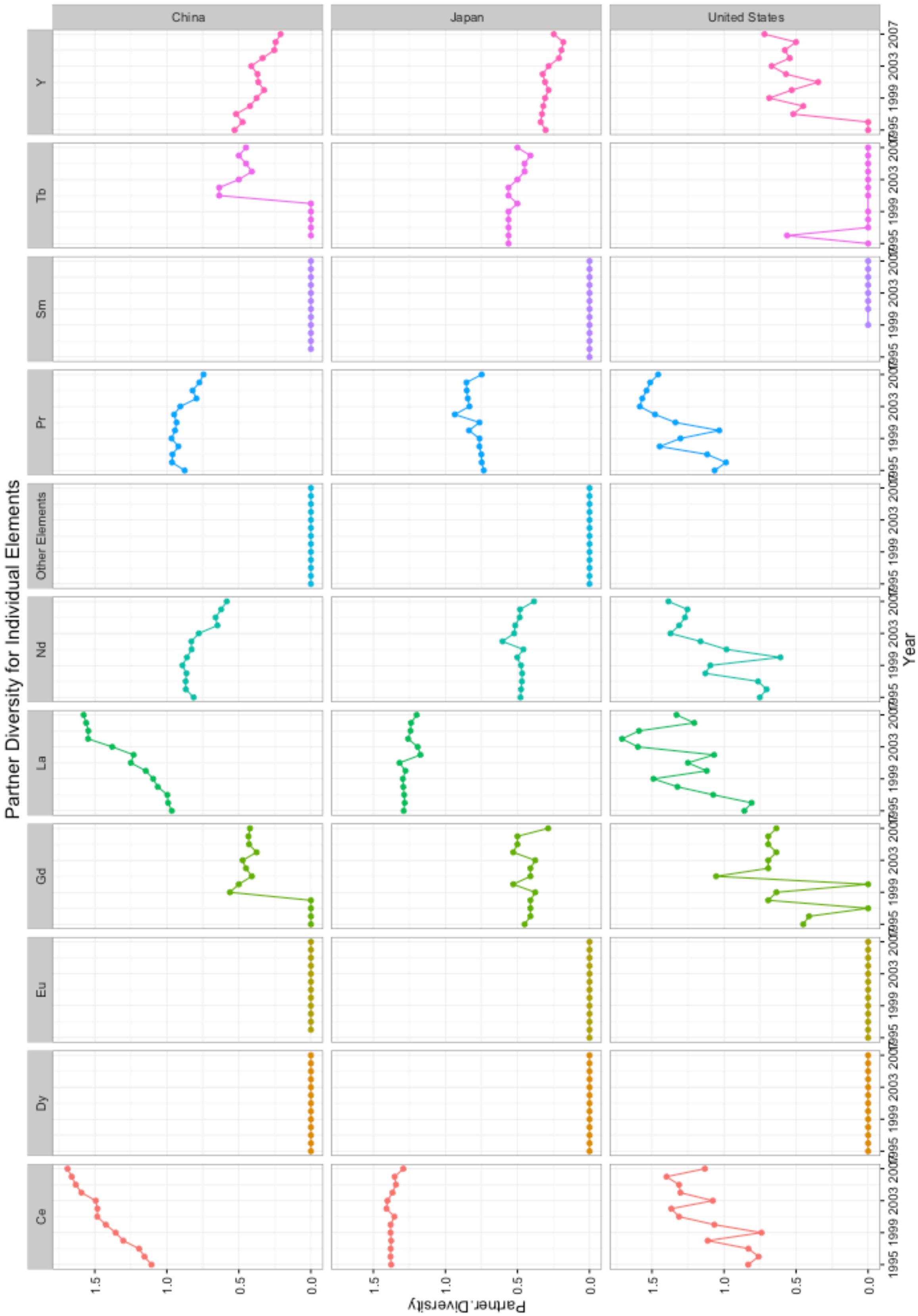

Figure 39. Partner Diversity Figure Enlarged

C-2. Connectance

```
t <- ggplot(network_results, aes(Year, Connectance))
t + geom_point(aes(size=3), shape=5) + geom_line() + facet_wrap(~ Country, scales="fixed") + theme_bw(base_family = "", base_size = 18) + labs(x = "Year") + labs(y = "Connectance") + labs(title = "Connectance by Country") + theme(legend.position="none") + coord_cartesian(xlim=(1994:2008)) + theme(panel.margin = unit(2.5, "char"))
```

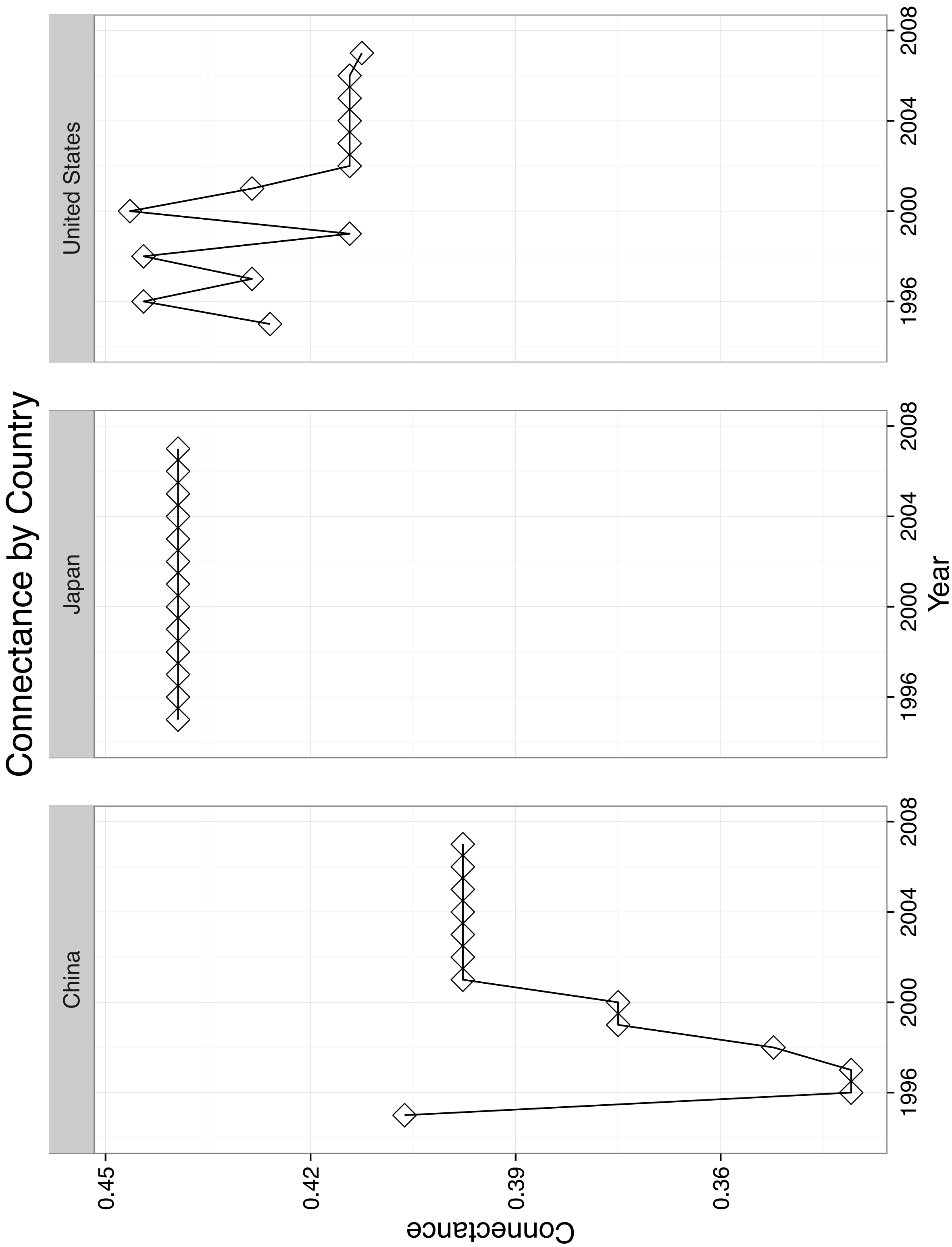

Figure 40. Connectance Full – Landscape

C-3. Specialization Asymmetry

```
t <- ggplot(network_results, aes(Year, Specialisation.Asymmetry))
t + geom_point(aes(size=3), shape=17) + geom_line() + facet_wrap(~ Country, scales="fixed") + theme_bw(base_family = "", base_size = 18) + labs(x = "Year") + labs(y = "Specialisation Asymmetry") + labs(title = "Specialisation Asymmetry by Country") + theme(legend.position="none") + coord_cartesian(xlim=(1994:2008)) + theme(panel.margin = unit(2.5, "char"))
```

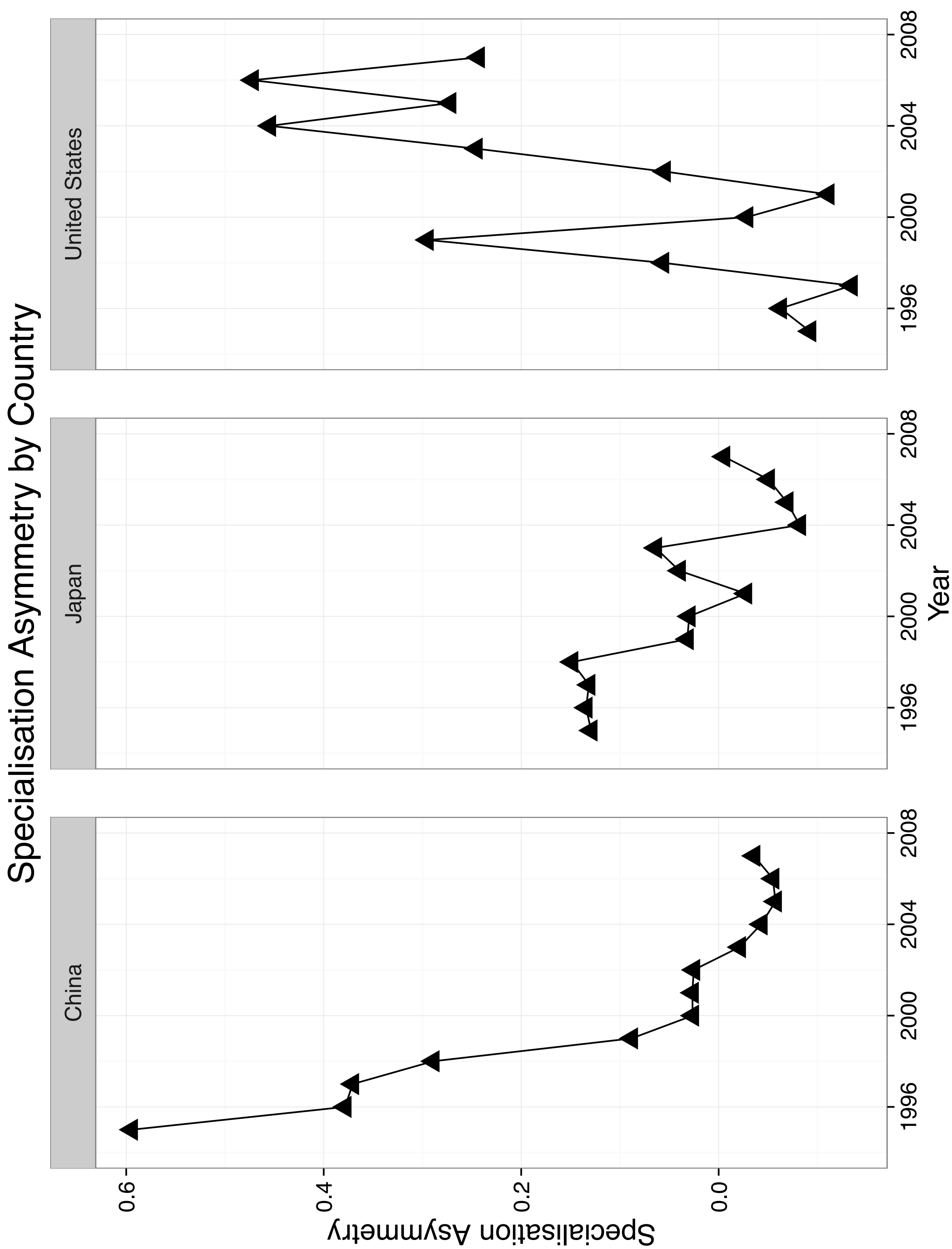

Figure 41. Specialization Asymmetry Full - Landscape

C-4. Vulnerability

```
t <- ggplot(group_results, aes(Year, Vulnerability.LL))
t + geom_point(aes(size=3), shape=15) + geom_line() + facet_wrap(~ Country, scales="fixed") + theme_bw(base_family = "", base_size = 18) + labs(x = "Year") + labs(y = "Vulnerability") + labs(title = "Vulnerability for Element Group by Country") + theme(legend.position="none") + coord_cartesian(xlim=(1994:2008)) + theme(panel.margin = unit(2.5, "char"))
```

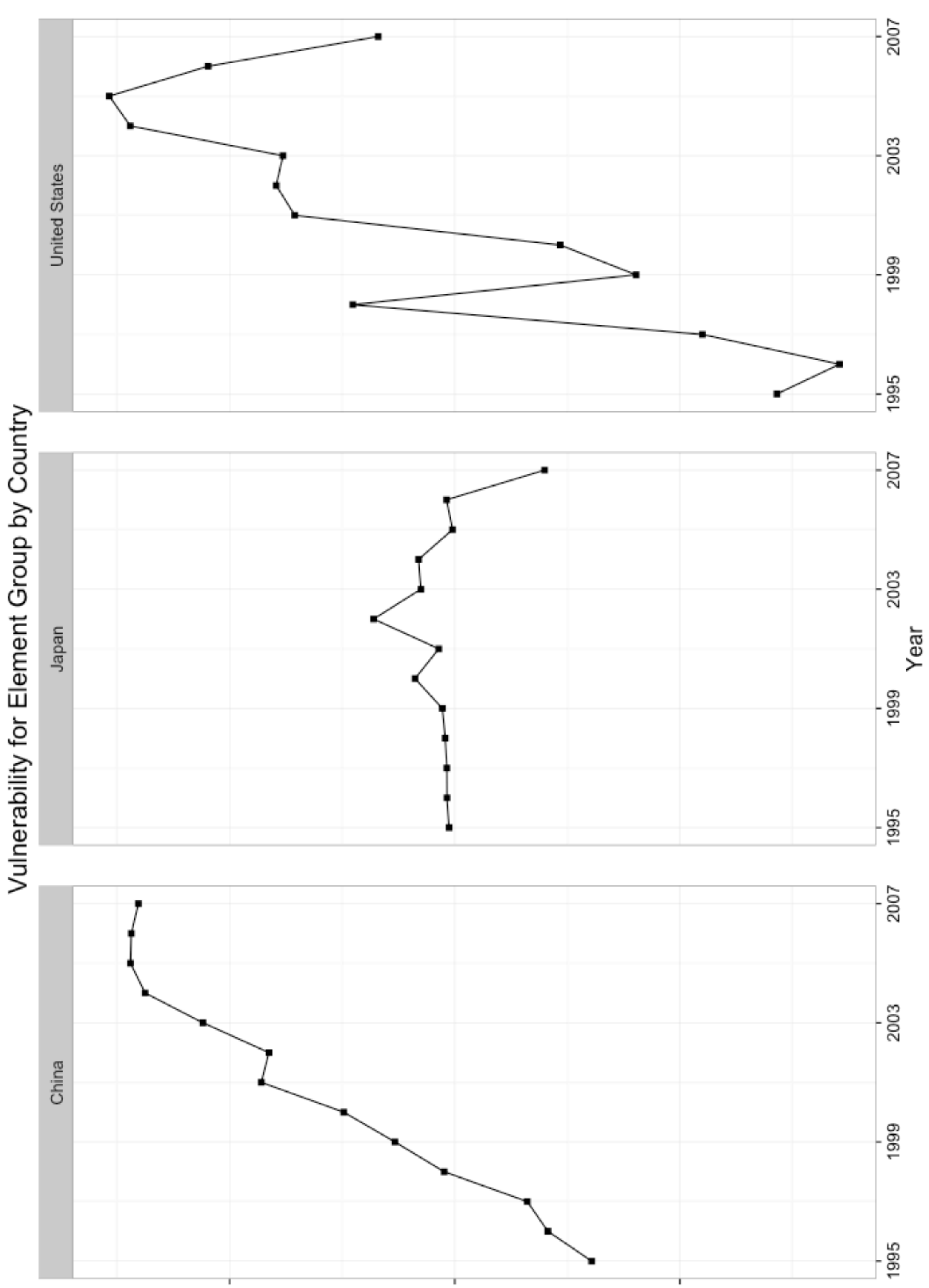

Figure 42. Vulnerability Figure Enlarged

C-5. Extinction Slope

```
t <- ggplot(group_results, aes(Year, Extinction.Slope.HL))
t +  geom_point(aes(size=2), shape=6) + geom_line() + facet_wrap(~ Country, scales="fixed") +
theme_bw(base_family = "", base_size = 18) + labs(x = "Year") + labs(y = "Extinction Slope") +
labs(title = "Extinction Slope for Products by Country") + theme(legend.position="none") +
coord_cartesian(xlim=(1994:2008)) + theme(panel.margin = unit(2.5, "char"))
```

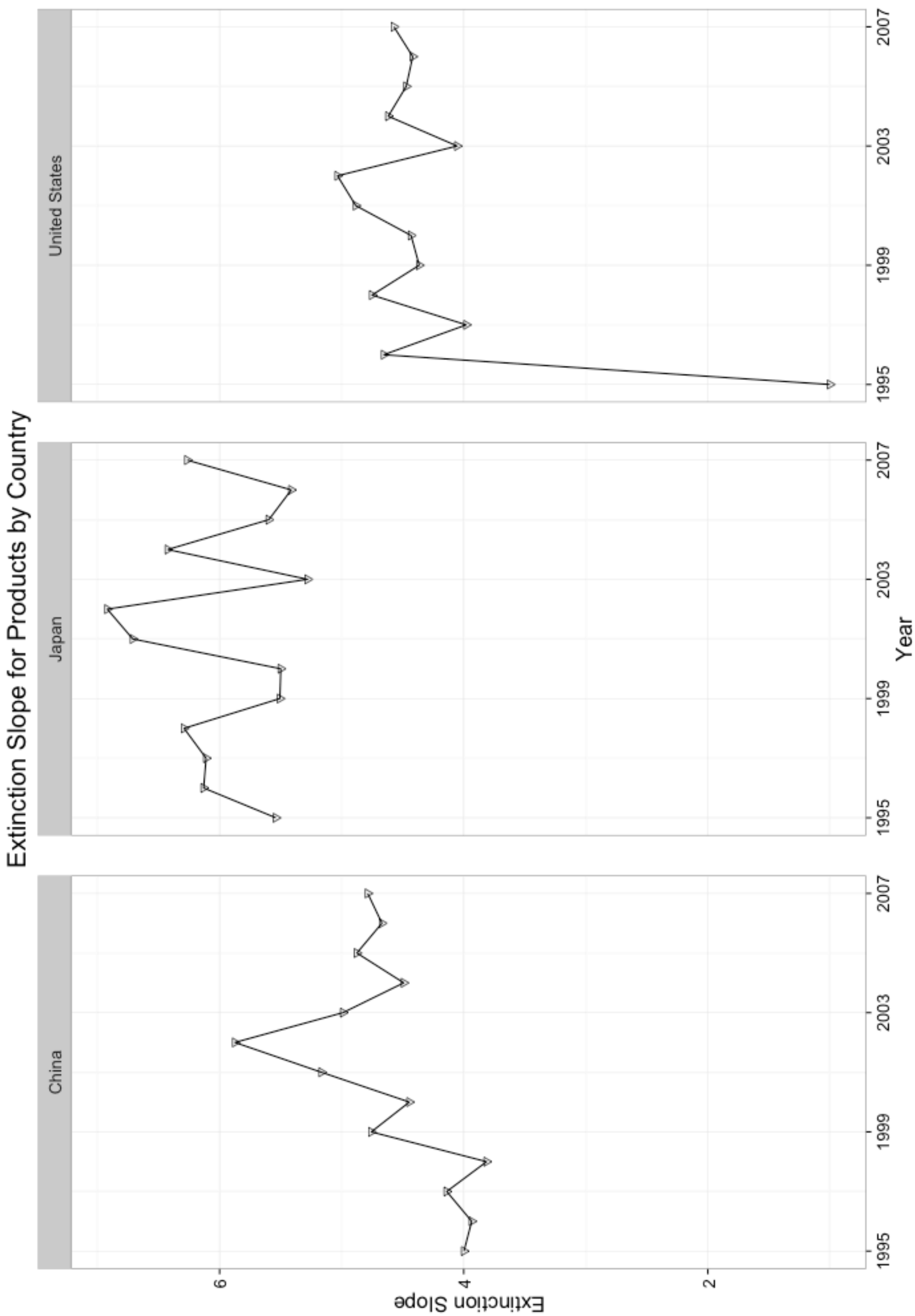

Figure 43. Extinction Slope Figure Enlarged

C-6. d’

```
# Landscape
g <- ggplot(element_species, aes(x=Year, y=d, fill=Element.or.Product)) +
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("d' for Individual Elements by Country") +
    facet_grid(facets=Country ~ Element.or.Product) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(color="black")) +
    theme(panel.grid = element_blank()) +
    theme_bw() +
    theme(legend.position="none")

g
```

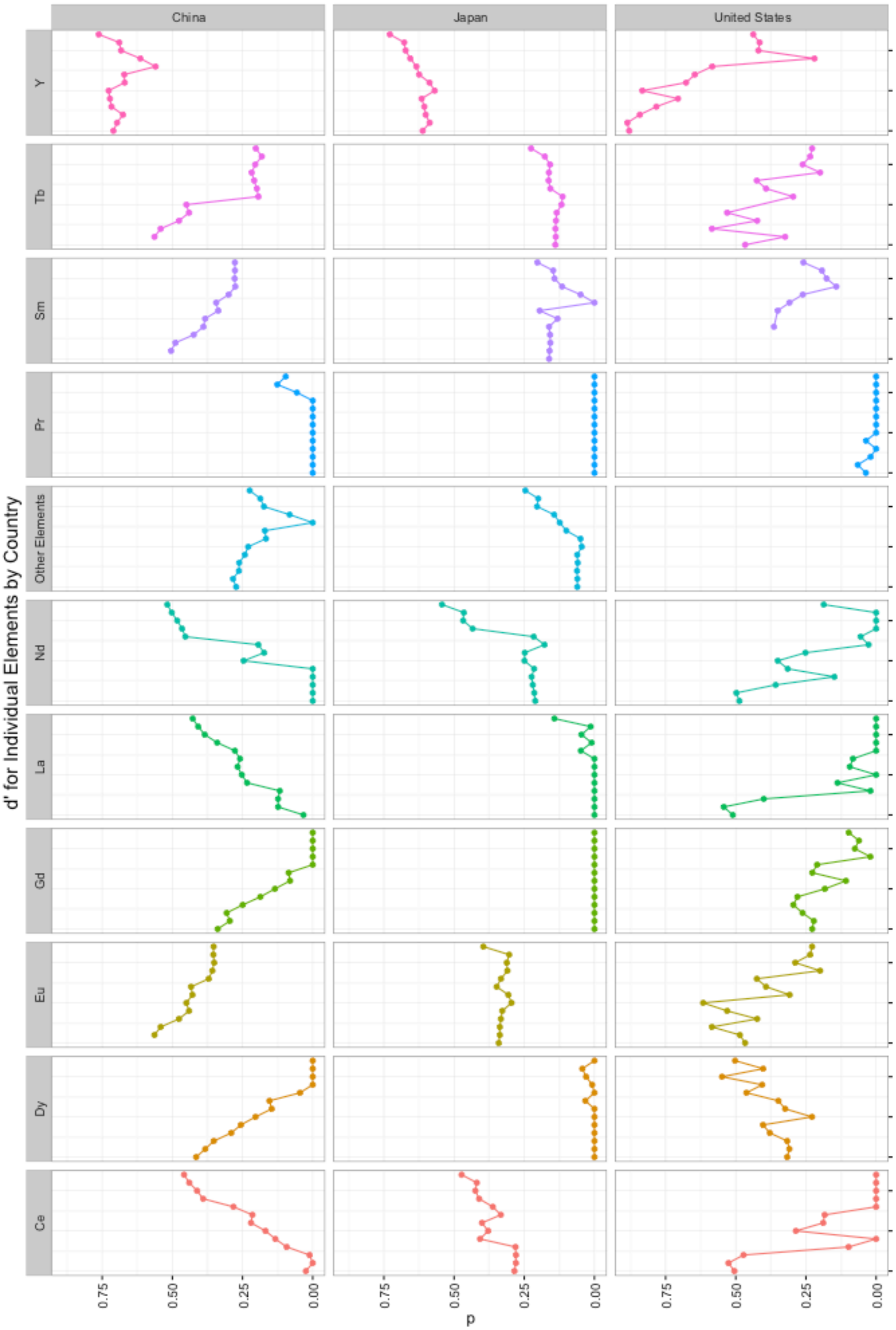

Figure 44. d' Figure Enlarged

C-7. Cluster Coefficient – Network- and Group-level

```
# Network-level
g <- ggplot(network_results, aes(Year, Cluster.Coefficient)) +
    geom_point(size=2) +
    geom_line(aes(method="lm")) +
    labs(title = "Cluster Coefficient by Country") +
    facet_grid(facets=. ~ Country, drop=TRUE) +
    labs(y = "Cluster Coefficient") +
    labs(x = "Year") +
    guides(size=FALSE) +
    theme_bw(base_family = "", base_size=18) +
    scale_x_continuous(breaks=seq(1995,2007,4)) +
    theme(panel.margin = unit(2.5, "char"))
g
```

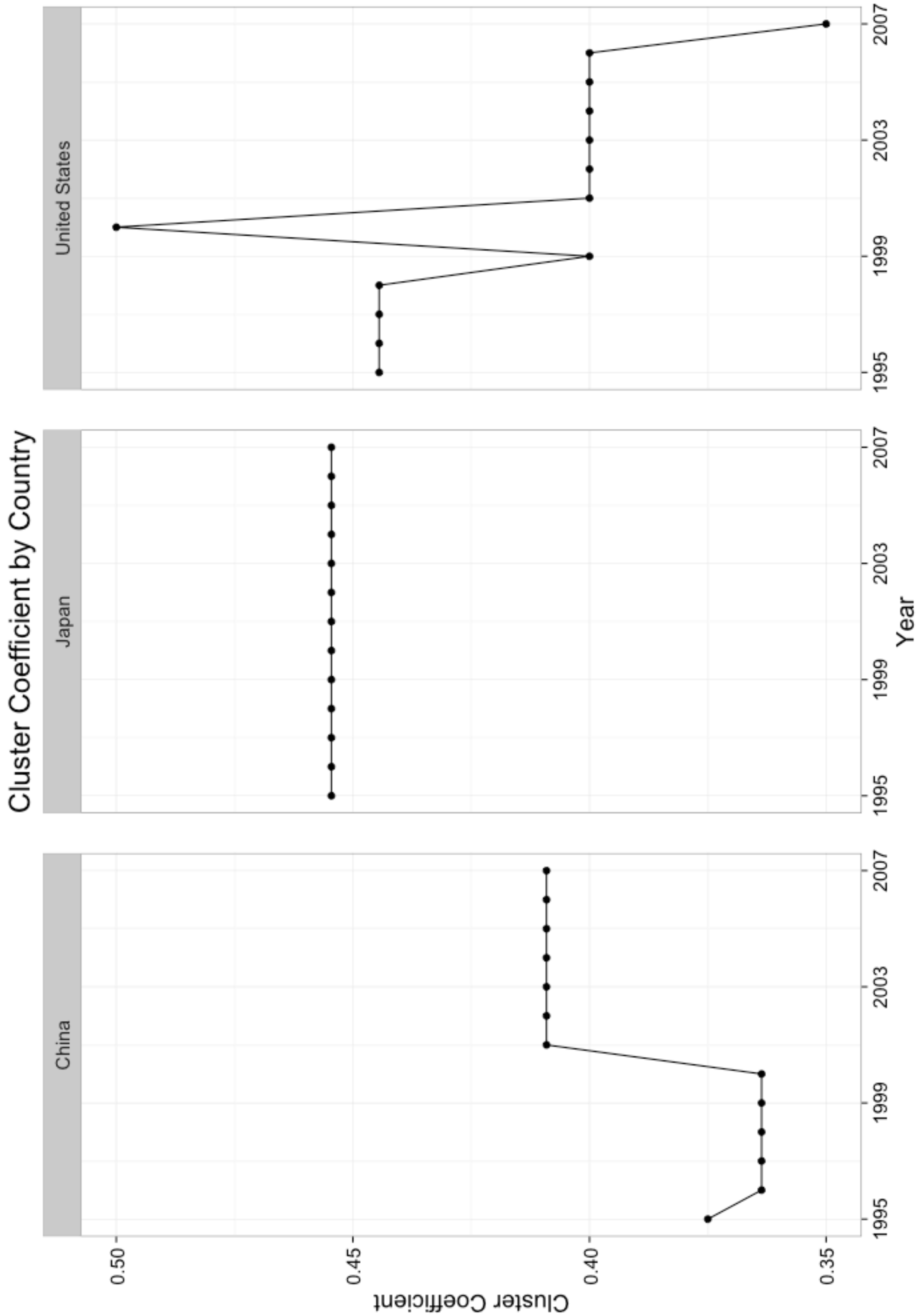

Figure 45. Cluster coefficient network-level Figure Enlarged

```
# Group-level LL
t <- ggplot(group_results2, aes(Year, Cluster.Coefficient.LL))
t +  geom_point(size=2, shape=9) + geom_line() + facet_wrap(~ Country, scales="fixed") + theme_bw(base_family = "", base_size = 12) + labs(x = "Year") + labs(y = "Lower-level Cluster Coefficient") + labs(title = "Cluster Coefficient for Element Group by Country") + theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,4)) + theme(panel.margin = unit(2.5, "char"))
```

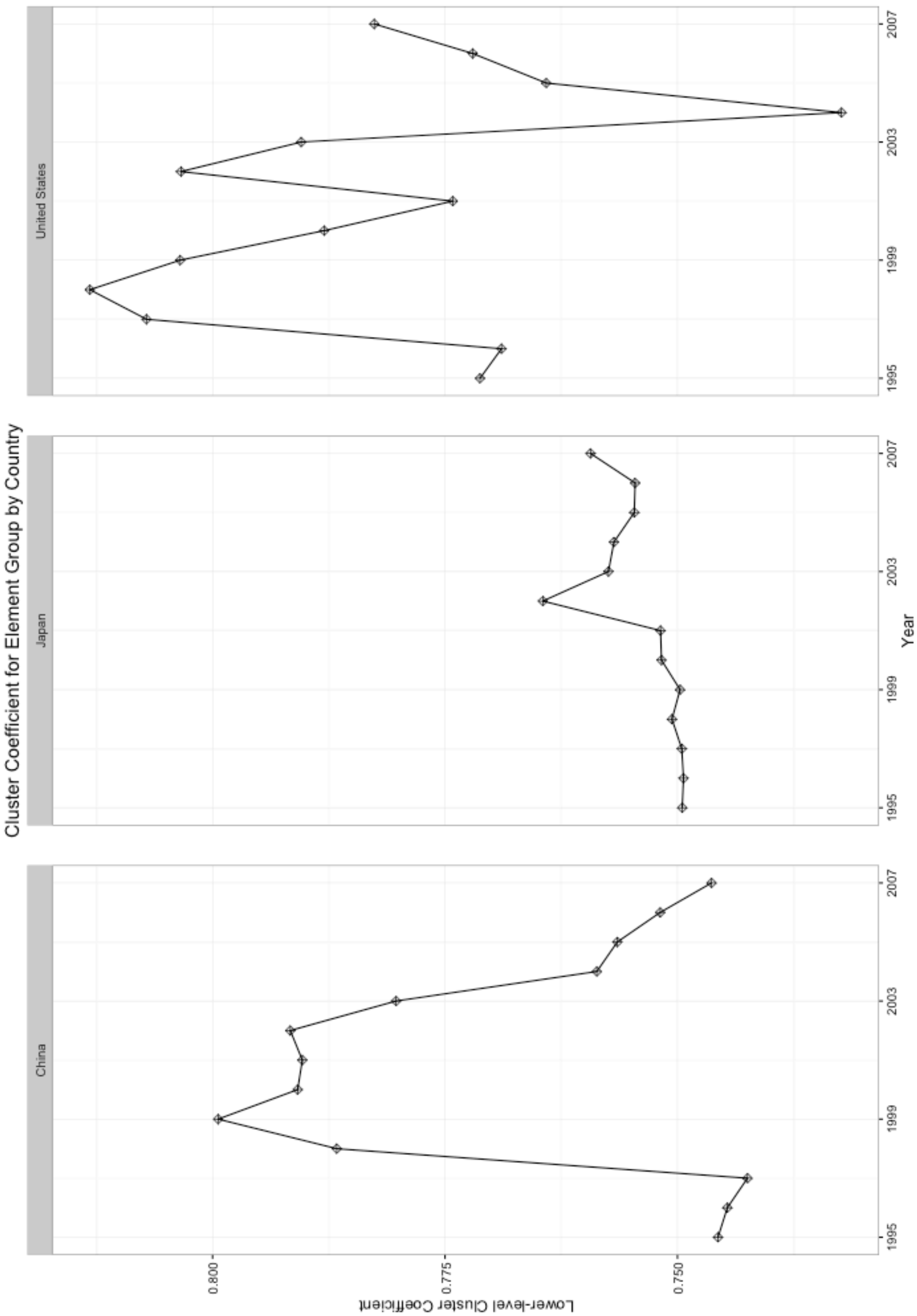

Figure 46. Cluster coefficient for the group-level (LL) Figure Enlarged

# Group-level LL
t <- ggplot(group_results2, aes(Year, Cluster.Coefficient.HL))
t + geom_point(size=2, shape=12) + geom_line() + facet_wrap(~ Country, scales="fixed") + theme_bw(base_family = "", base_size = 12) + labs(x = "Year") + labs(y = "Higher-level Cluster Coefficient") + labs(title = "Cluster Coefficient for Product Group by Country") + theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,4)) + theme(panel.margin = unit(2.5, "char"))

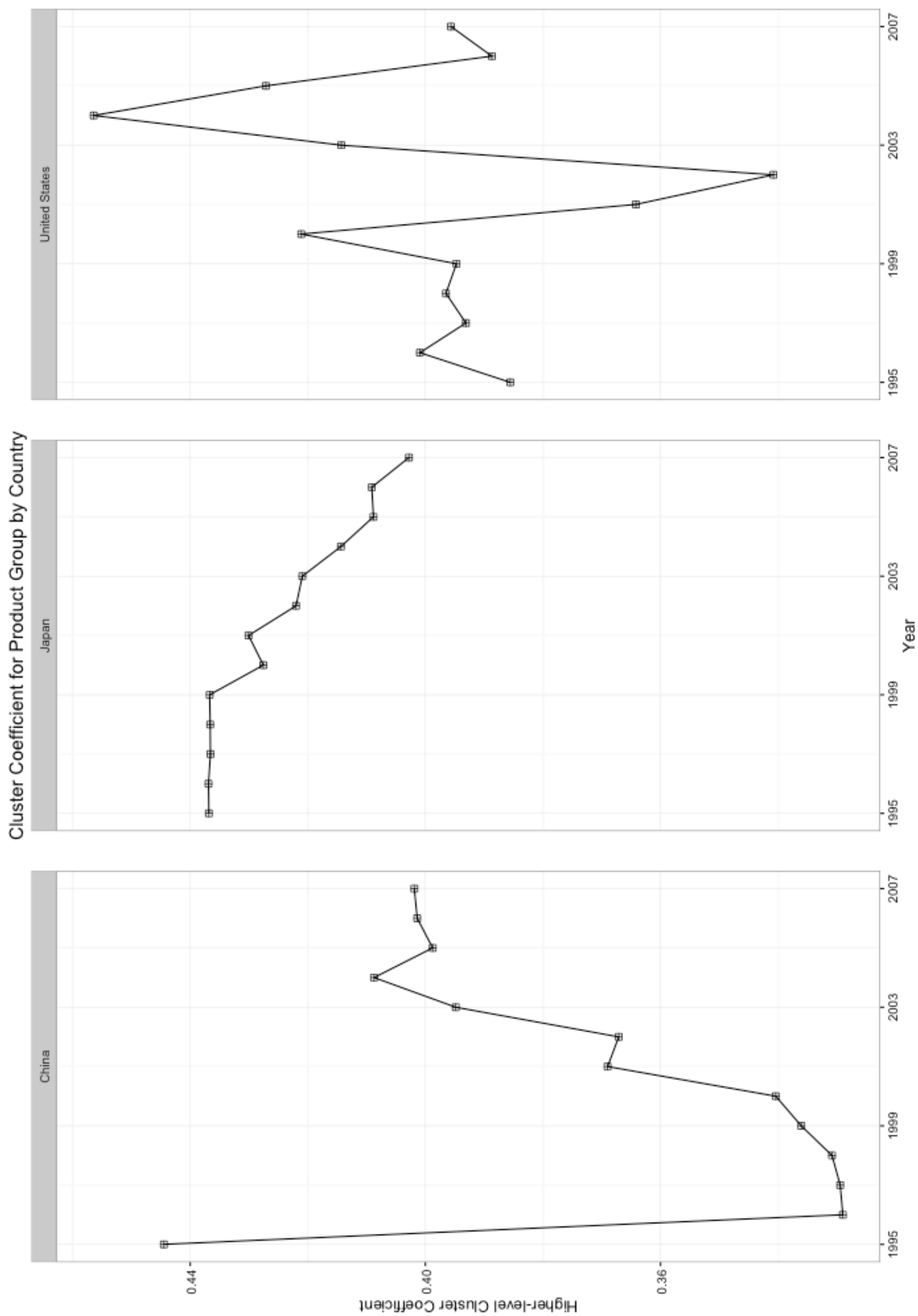

Figure 47. Cluster coefficient for the group level (HL) Figure Enlarged

C-8. Shannon Diversity

```
t <- ggplot(network_results, aes(Year, Shannon.Diversity))
t + geom_point(size=2, shape=6) + geom_line() + facet_wrap(~ Country, scales="fixed") + theme_bw(base_family = "", base_size = 16) + labs(x = "Year") + labs(y = "Shannon Diversity") + labs(title = "Shannon Diversity by Country") + theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,4)) + theme(panel.margin = unit(2.5, "char"))
```

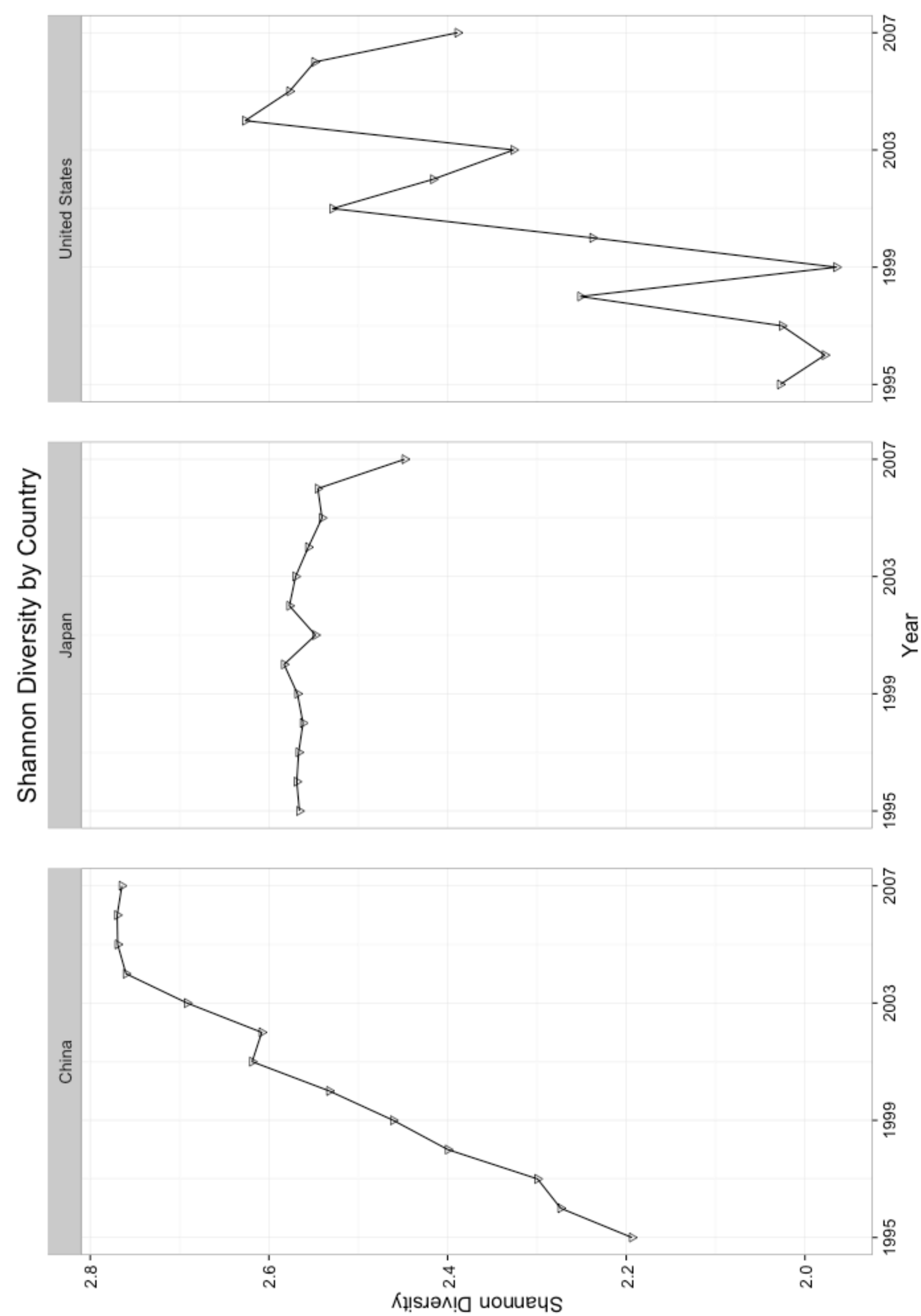

Figure 48. Shannon diversity Figure Enlarged

C-9. Niche Overlap

```
t <- ggplot(group_results2, aes(Year, Niche.Overlap.LL))
t + geom_point(size=2, shape=15) + geom_line() + facet_wrap(~ Country, scales="fixed") + theme_bw(base_family = "", base_size = 12) + labs(x = "Year") + labs(y = "Lower-level Niche Overlap") + labs(title = "Niche Overlap for Element Group by Country") + theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,4)) + theme(panel.margin = unit(2.5, "char"))
```

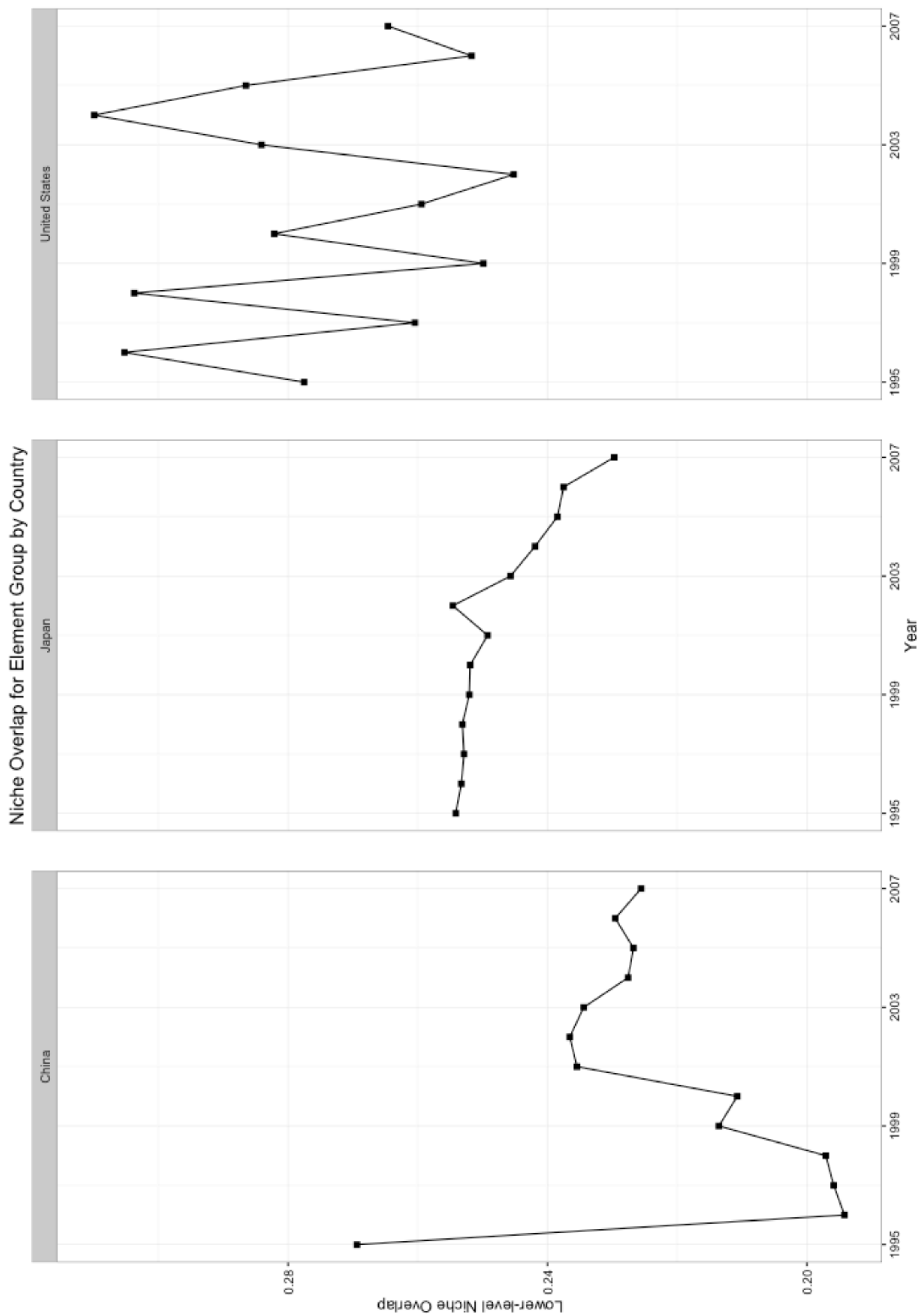

Figure 49. Niche overlap Figure Enlarged

C-10. Normalized Degree

```
# Element
g <- ggplot(element_species2, aes(x=Year, y=Normalised.Degree, fill=Element.or.Product)) +
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("Normalized Degree for Individual Elements by Country") +
    facet_grid(facets=Country ~ Element.or.Product) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(color="black")) +
    theme(panel.grid = element_blank()) +
    theme_bw() +
    theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,5))
g
```

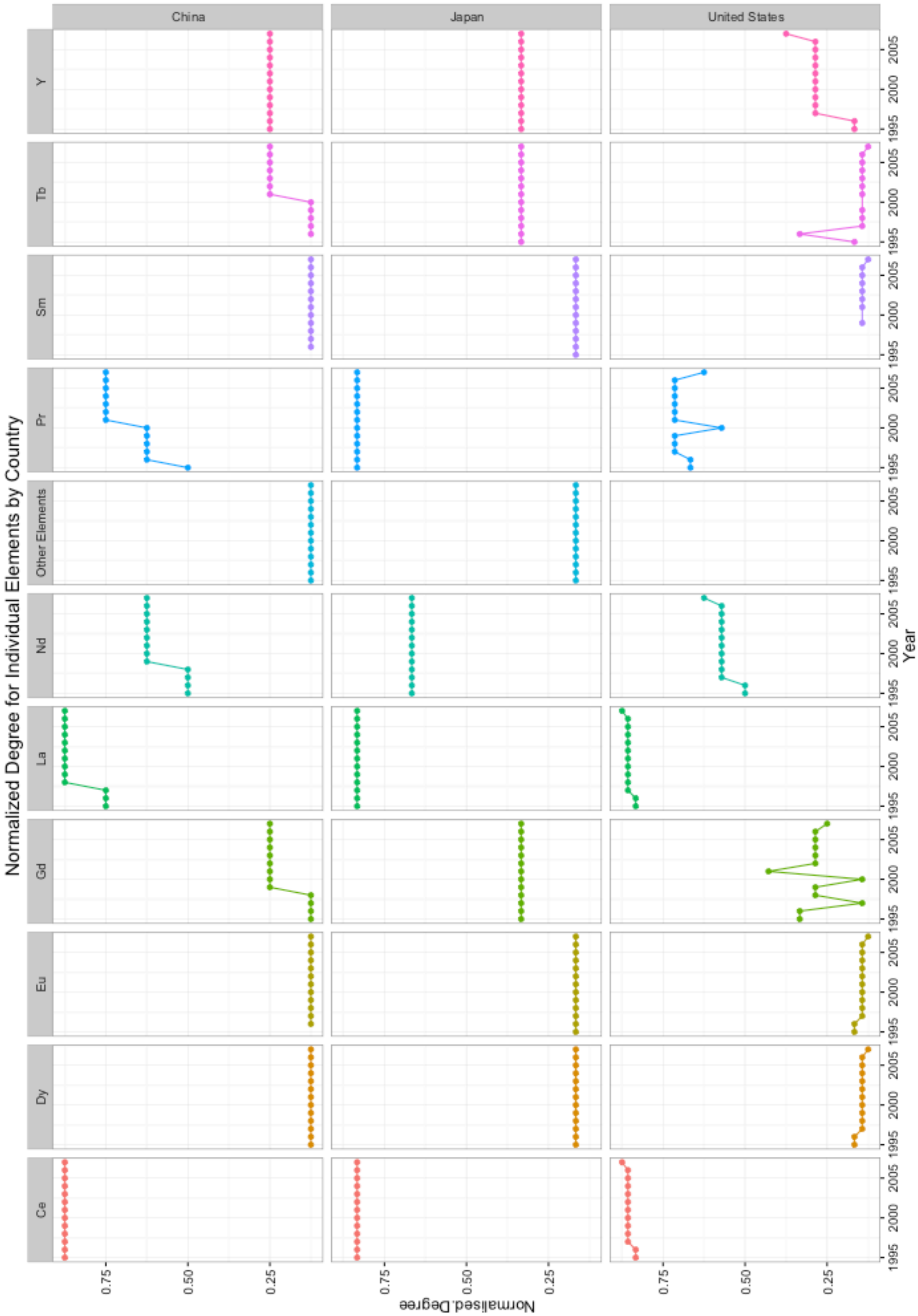

Figure 50. Normalized degree for Individual Elements Figure Enlarged

```
# Product
g <- ggplot(product_species2, aes(x=Year, y=Normalised.Degree, fill=Element.or.Product)) +
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("Normalized Degree for Individual Products by Country") +
    facet_grid(facets=Country ~ Element.or.Product) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(color="black")) +
    theme(panel.grid = element_blank()) +
    theme_bw() +
    theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,5))
g
```

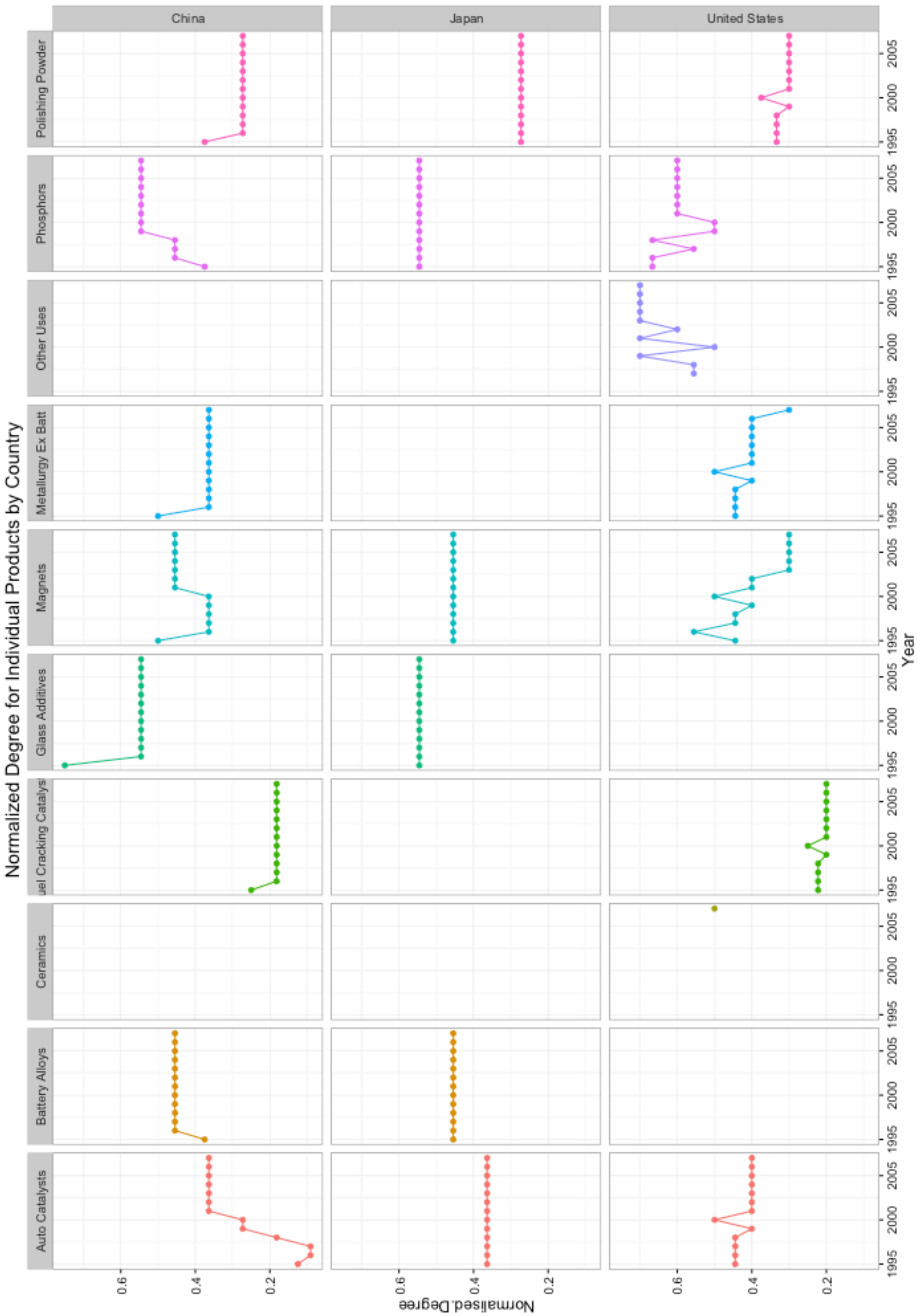

Figure 51. Normalized degree for Individual Products Figure Enlarged

C-11. Interaction Push-Pull

```
# Element Species
g <- ggplot(element_species2, aes(x=Year, y=Interaction.Push.Pull, fill=Element.or.Product)) +
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("Interaction Push-Pull for Individual Elements by Country") +
    facet_grid(facets=Country ~ Element.or.Product) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(color="black")) +
    theme(panel.grid = element_blank()) +
    theme_bw() +
    theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,5))
g
```

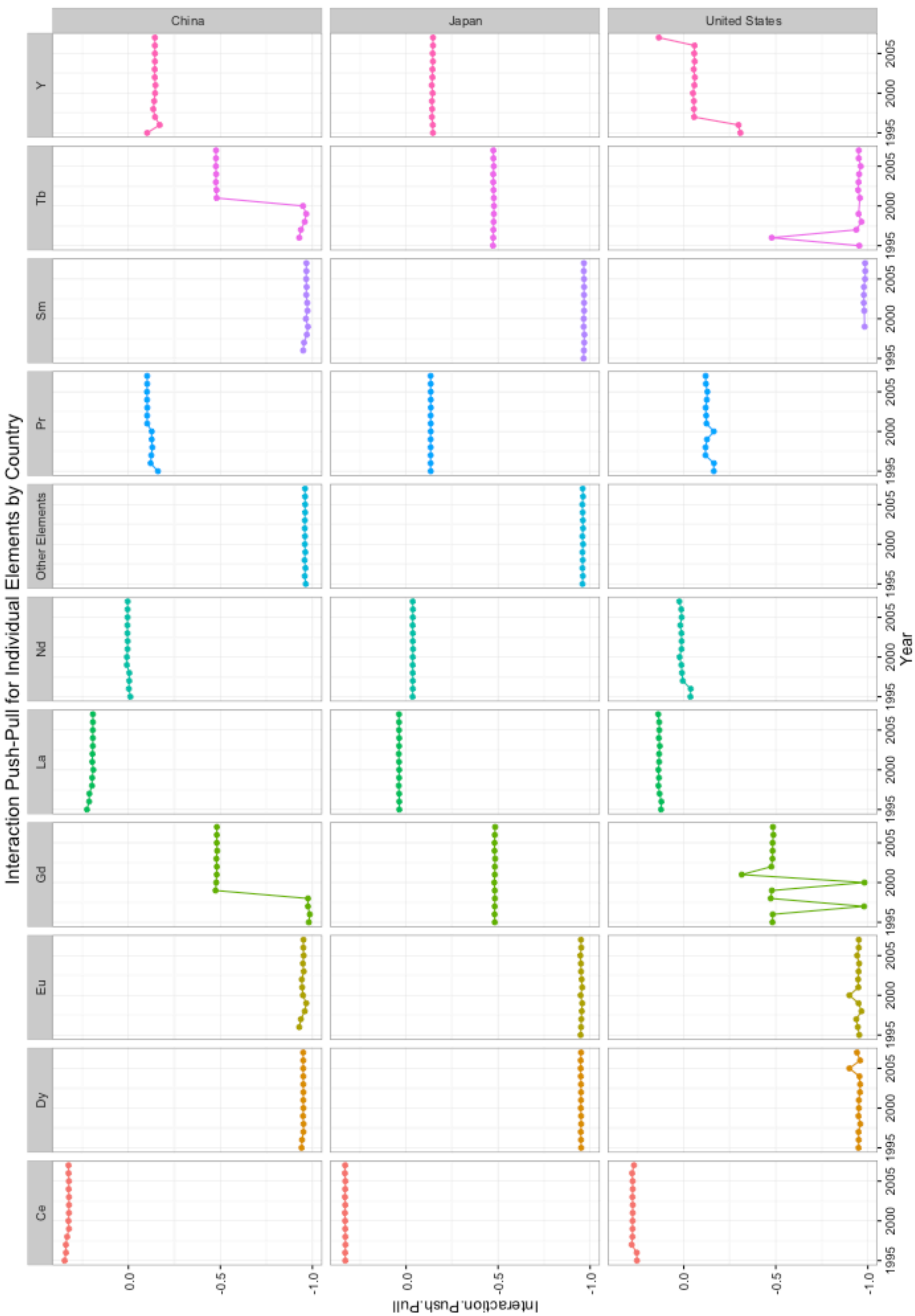

Figure 52. Interaction Push-Pull Element Species Figure Enlarged

```
# Product Species
g <- ggplot(product_species2, aes(x=Year, y=Interaction.Push.Pull, fill=Element.or.Product)) +
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("Interaction Push-Pull for Individual Products by Country") +
    facet_grid(facets=Country ~ Element.or.Product) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(color="black")) +
    theme(panel.grid = element_blank()) +
    theme_bw() +
    theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,5))
g
```

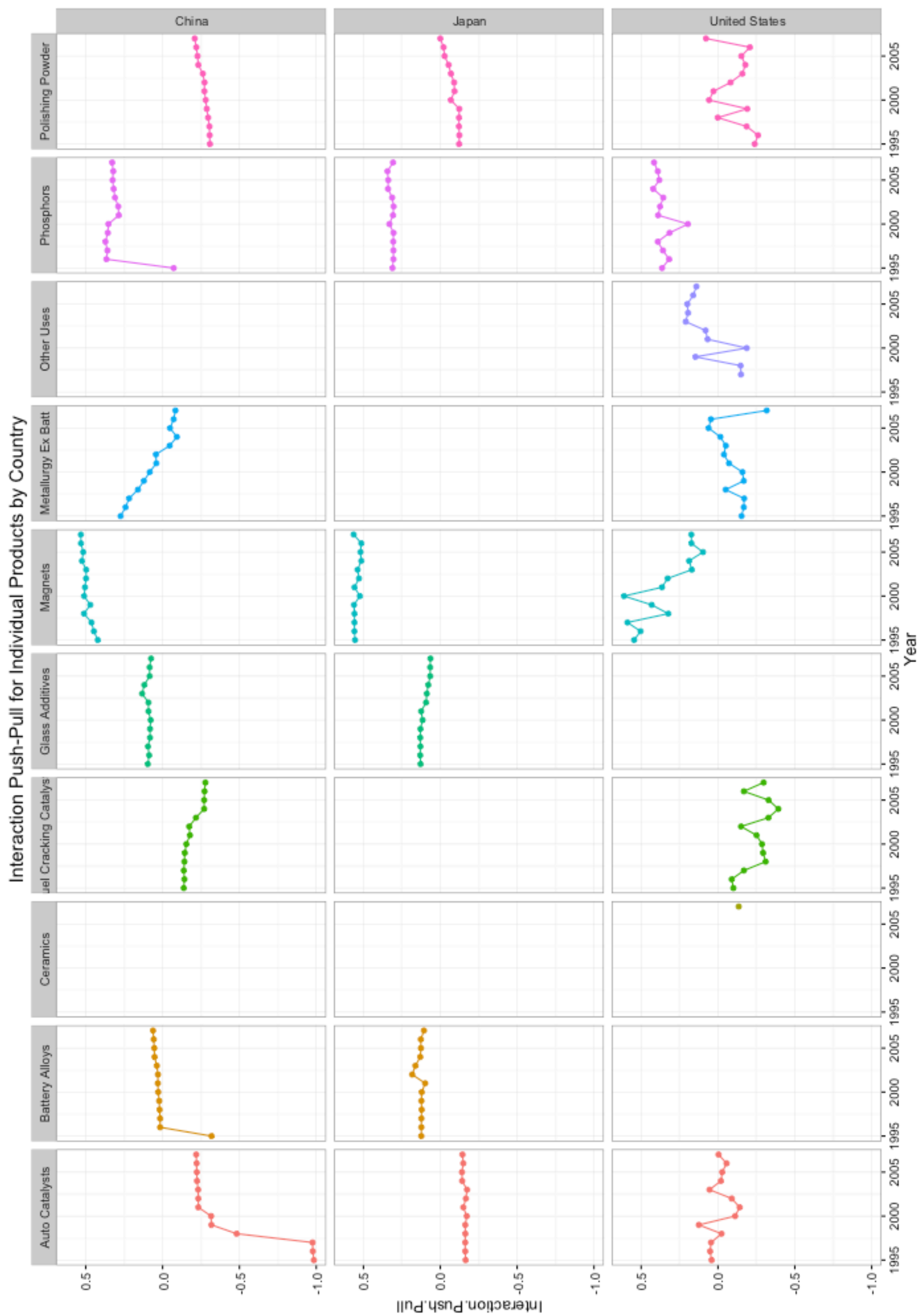

Figure 53. Interaction Push-Pull Product Species Figure Enlarged

C-12. Weighted Betweennness

```
# Element Species
g <- ggplot(element_species2, aes(x=Year, y=Weighted.Betweenness, fill=Element.or.Product))
+
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("Weighted Betweenness for Individual Elements by Country") +
    facet_grid(facets=Country ~ Element.or.Product) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(color="black")) +
    theme(panel.grid = element_blank()) +
    theme_bw() +
    theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,5))

g
```

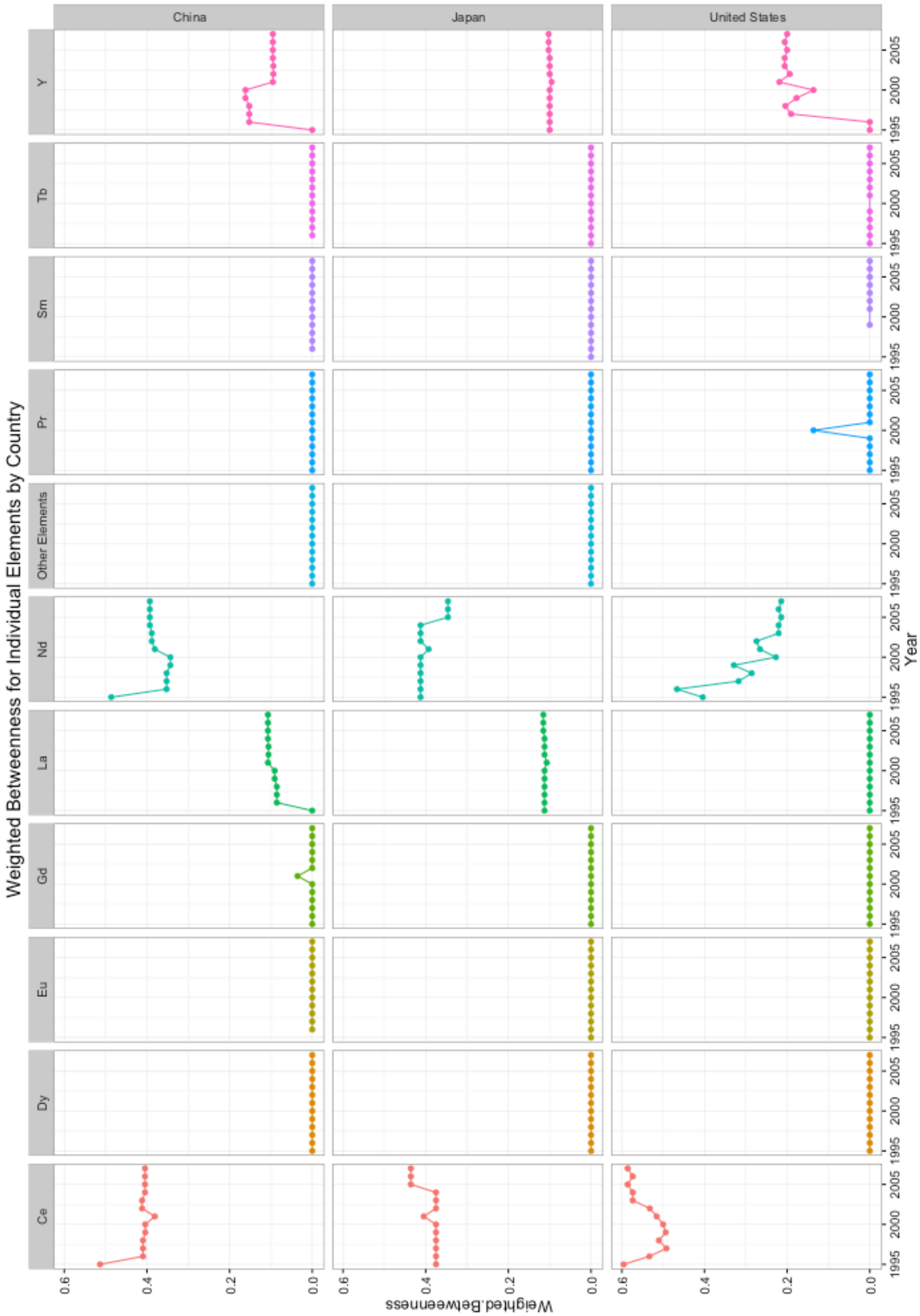

Figure 54. Weighted Betweenness Element Species Figure Enlarged

```
# Product Species
g <- ggplot(product_species2, aes(x=Year, y=Weighted.Betweenness, fill=Element.or.Product)) +
    geom_point(aes(color=Element.or.Product)) +
    geom_line(aes(color= Element.or.Product, method="lm")) +
    ggtitle("Weighted Betweenness for Individual Products by Country") +
    facet_grid(facets=Country ~ Element.or.Product) +
    theme(panel.background = element_blank()) +
    theme(panel.background = element_rect(color="black")) +
    theme(panel.grid = element_blank()) +
    theme_bw() +
    theme(legend.position="none") + scale_x_continuous(breaks=seq(1995,2007,5))
g
```

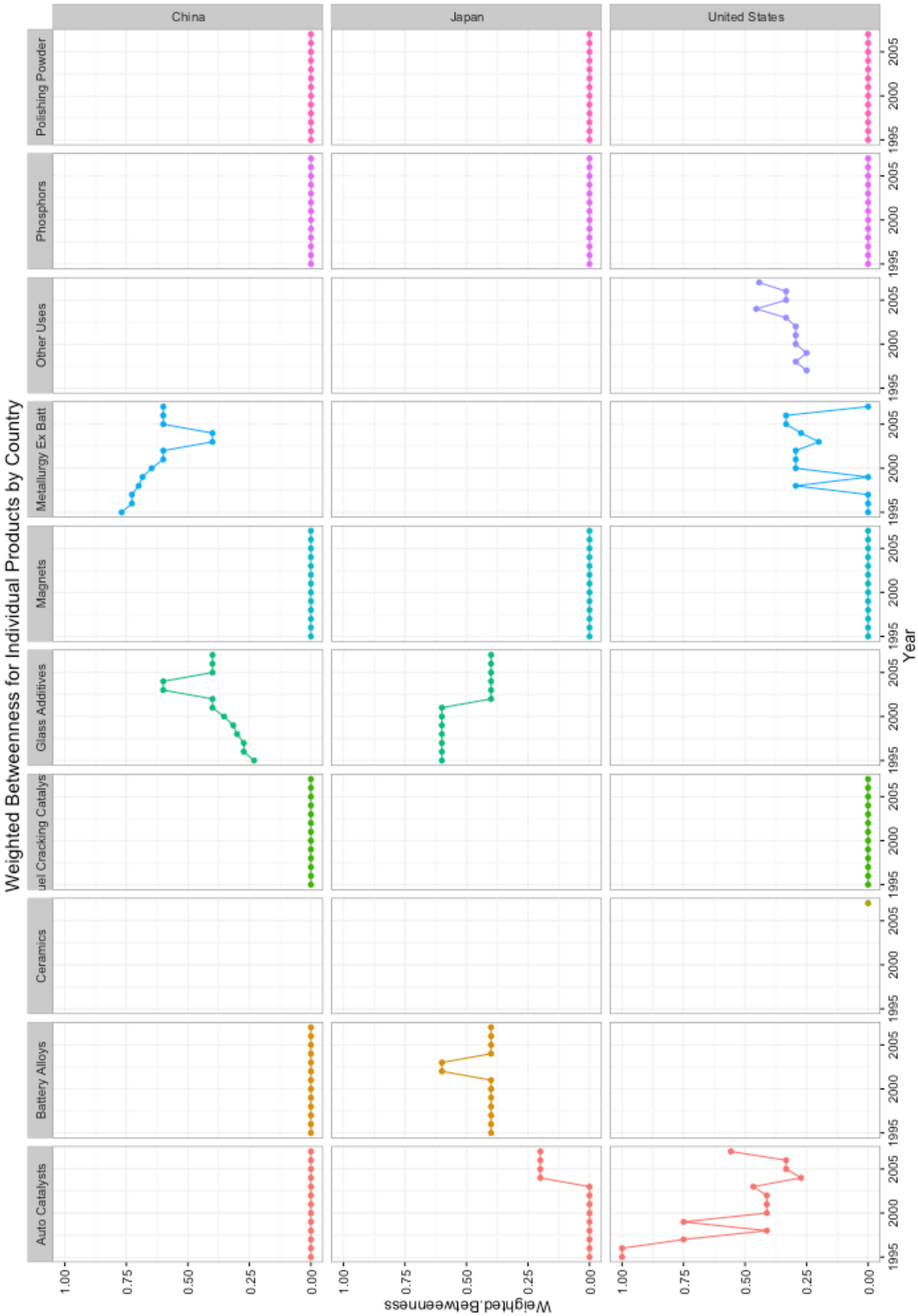

Figure 55. Weighted Betweenness Product Species Figure Enlarged

APPENDIX D. Sample R Code

D-1. Sample Data File

Data files were saved in the format "COUNTRYyear.csv" and analyzed using the R code in Appendix D-2.

For "US2000.csv", the data file is as shown:

Table 11. Sample data file for R code

	Magnets	Battery Alloys	Metallurgy ex.batt	Auto Catalysts	FCC	Polishing Powder	Glass Additives	Phosphors	Ceramics	Others
Y	0	0	0	0	0	0	0.03	0.27	0	0
La	0	0.28	1.16	0.01	3.31	0.21	0.41	0.03	0	0
Ce	0	0.18	2.31	0.22	0.37	0.44	1.13	0.04	0	0
Pr	0.48	0.02	0.24	0	0	0.02	0.02	0	0	0
Nd	1.43	0.06	0.73	0.01	0	0	0.05	0	0	0
Sm	0	0.02	0	0	0	0	0	0	0	0
Eu	0	0	0	0	0	0	0	0.02	0	0
Gd	0.04	0	0	0	0	0	0	0.01	0	0
Tb	0	0	0	0	0	0	0	0.02	0	0
Dy	0.1	0	0	0	0	0	0	0	0	0
Others	0	0	0	0	0	0	0.07	0	0	0

D-2. Sample Bipartite Metric Script

This code generates results for each country, year, and every level of metric. This sample is for the US data.

```
library(bipartite)
#start loop here
years <- rbind(1995:2007)
years

for (i in 1:length(years))
{
    file_name <- paste("US", years[1, i], ".csv", sep = "")
    WEB <- read.csv(file_name, row.names=1)

    # sort web by most abundant
    file_name <- paste("sortedWEB_US", years[1, i], ".csv", sep = "")
    sortedWEB <- sortweb(WEB, sort.order="dec", sequence=NULL)
    write.csv(sortedWEB, file=file_name)

    # generate heat map graphic
    file_name <- paste("heat_map_US", years[1, i], ".jpg", sep = "")
    jpeg(file_name)

    visweb(sortedWEB,type="nested",prednames=TRUE,preynames=TRUE,labsize=1,plotsize=
    12,square="interaction",text="no",frame=NULL,textsize=1,textcol="red",pred.lablength=NU
    LL, prey.lablength=NULL, clear=TRUE, xlabel="", ylabel="", boxes=TRUE,
    circles=FALSE, circle.col="black", circle.min=0.2, circle.max=2, outerbox.border="white",
    outerbox.col="white", box.border="black", box.col="black",
    def.col="blue",max.digits=4,NA.col="red")
    dev.off()

    # generate sankey diagram graphic
    file_name <- paste("sankey_US", years[1, i], ".jpg", sep = "")
    jpeg(file_name)
    plotweb(sortedWEB, method = "cca", empty = TRUE, labsize = 1, ybig = 1,  y.width.low =
    0.1, y.width.high = 0.1, low.spacing = NULL, high.spacing = NULL, arrow="no",
    col.interaction="grey80", col.high = "grey10", col.low="grey10",  bor.col.interaction
    ="black", bor.col.high="black", bor.col.low="black", high.lablength = NULL, low.lablength =
```

```
    NULL, sequence=NULL, low.abun=NULL, low.abun.col="green", bor.low.abun.col
    ="black", high.abun=NULL, high.abun.col="red", bor.high.abun.col="black", text.rot=0,
    text.high.col="black", text.low.col="black", adj.high=NULL, adj.low=NULL, plot.axes =
    FALSE, low.y=0.5, high.y=1.5, add=FALSE, y.lim=NULL, x.lim=NULL, low.plot=TRUE,
    high.plot=TRUE, high.xoff = 0, low.xoff = 0, high.lab.dis = NULL, low.lab.dis = NULL,
    abuns.type="additional")
    dev.off()

    # three levels of analysis: 1) network, 2) group, and 3) species
    # each level has a different set of indices

    # network-level analysis (entire matrix)
    file_name <- paste("network_US", years[1, i], ".csv", sep = "")
    networklevel <- networklevel(sortedWEB, index="ALLBUTDD", level="both",
    weighted=TRUE, ISAmethod="Bluethgen", SAmethod = "Bluethgen", extinctmethod = "r",
    nrep = 100, CCfun=median, dist="horn", normalise=TRUE, empty.web=TRUE, logbase="e",
    intereven="prod", H2_integer=TRUE, fcweighted=TRUE, fcdist="euclidean",
    legacy=FALSE)
    write.csv(networklevel, file=file_name)

    # group-level analysis (each group [elements, products] separately)
    # HL - is higher level or products, LL - is lower level or elements

    file_name <- paste("group_US", years[1, i], ".csv", sep = "")
    grouplevel <- grouplevel(sortedWEB, index="ALLBUTDD", level="both", weighted=TRUE,
    empty.web=TRUE, dist="horn", CCfun=mean, logbase="e", normalise=TRUE,
    extinctmethod="r", nrep=100, fcdist="euclidean", fcweighted=TRUE)
    write.csv(grouplevel, file=file_name)

    # species-level analysis (individual elements and products)
    file_name <- paste("species_US", years[1, i], ".csv", sep = "")
    specieslevel <- specieslevel(sortedWEB, index="ALLBUTD", level="both", logbase=exp(1),
    low.abun=NULL, high.abun=NULL, PDI.normalise=TRUE, PSI.beta=c(1,0),
    nested.method="NODF", nested.normalised=TRUE, nested.weighted=TRUE,
    empty.web=TRUE)
    specieslevel.df <- do.call("rbind", lapply(specieslevel, as.data.frame))
    write.csv(file = file_name, specieslevel.df)
}
```

D-3. Sample Code for Concatenating Network Results

This code joins the network metric results for each year, sample shown is for the US data.

```
## Combine Data Tables
# start loop

years <- rbind(1995:2007)
years

for (i in 1:length(years))
{
    # create pass through file
    file_name <- paste("network_US.csv")

    # store master data file as variable
    master_network_data <- read.csv("network_US.csv")

    # paste network data file for year i
    data_file <- paste("network_US", years[1,i], ".csv", sep = "")

    # read network data into variable for year i
    network_data_i <- read.csv(data_file)

    # combine master file and network data for year i
    network_data <- cbind(master_network_data, network_data_i[1:18,2])

    # write new data file to
    write.csv(network_data, file = file_name)

}

##
```

D-4. Sample Code for Concatenating Group Results

This code joins the group-level results for each year, sample shown is for the US data.

```
## Combine Data Tables
# start loop

years <- rbind(1995:2007)
years

for (i in 1:length(years))
{
    # create pass through file
    file_name <- paste("group_US.csv")

    # store master data file as variable
    master_group_data <- read.csv("group_US.csv")

    # paste group data file for year i
    data_file <- paste("group_US", years[1,i], ".csv", sep = "")

    # read group data into variable for year i
    group_data_i <- read.csv(data_file)

    # combine master file and group data for year i
    group_data <- cbind.data.frame(master_group_data, group_data_i[,2])

    # write new data file to
    write.csv(group_data, file = file_name)

}

##
```

D-5. Sample R Code for Generating Correlations, Correlation Figures, and Cluster

This code generates correlations based on Spearman's rank correlation coefficient, rho, and generates related figures and cluster analysis figures.

```
# Redundancy Analysis
# 1. Correlation with Spearman - and correlation plots
# 2. Cluster analysis plot with spearman^2

#############.1.####################
# check data to see which columns contain non-categorical variables
head(network_results, 2)
net_cor <- network_results[,2:19]

# need to ignore Number of compartments, compartment density, and Fisher alpha because
# they produce NA values that will not plot
net_cor2 <- cbind(net_cor[,1:3], net_cor[,6:13], net_cor[,15:18])

net_cor_table <- round(cor(net_cor2, method="spearman"), 3)
write.csv(net_cor_table, file = "~/Google Drive/Research - Working Files/Ecology/network_cor_spearman.csv")
dev.off()

net_cor_table <- round(cor(net_cor2, method="spearman"), 1)
ggcorrplot(net_cor_table, method = "square", type = "upper", ggtheme = ggplot2::theme_minimal,
        title = "Correlation of Network Level Metrics",
        show.legend = TRUE, show.diag = TRUE,
        colors = c("black", "white", "slateblue1"), outline.color = "white",
        hc.order = TRUE, hc.method = "complete", lab = TRUE,
        lab_col = "white", lab_size = 3, tl.cex = 10, tl.col = "black", tl.srt = 45)
```

```
ggsave("network_corr_plot_spearman.pdf", dpi = 600)

dev.copy(png, file="network_corr_plot_spearman.png", height=700, width=1000)

dev.off()

#############.2.####################

distance <- as.dist(round(cor(net_cor2, method="spearman"), 3))

spearman2 <- distance^2

plot(hclust(1-spearman2), main = expression(1-Spearman^(2)), xlab = "Network-Level Metric
Correlation")
```

APPENDIX E. Correlation Matrices for Metrics

The following tables are the source tables for the correlation figures within the text. Descriptions for how these values were determined are found within the methodology and results. Descriptions for how the plots were generated are found in Appendix D-5.

Table 12. Spearman's correlation matrix for Network-Level metrics

	Connectance	Web Asymmetry	Links Per Species	Cluster Coefficient	Nestedness	Weighted Nestedness	Weighted NODF	Interaction Strength Asymmetry	Specialisation Asymmetry	Linkage Density	Weighted Connectance	Shannon Diversity	Interaction Evenness	Alatalo Interaction Evenness	H2
Connectance	1	-0.589	-0.261	0.827	0.719	-0.823	-0.66	-0.063	-0.257	-0.381	0.218	-0.154	0.162	0.421	0.609
Web Asymmetry	-0.589	1	0.194	-0.63	-0.677	0.592	0.437	0.362	0.09	0.032	-0.175	-0.202	-0.428	-0.592	-0.523
Links Per Species	-0.261	0.194	1	-0.094	-0.02	0.367	0.292	-0.048	-0.252	0.695	0.333	0.66	0.478	0.194	-0.083
Cluster Coefficient	0.827	-0.63	-0.094	1	0.925	-0.776	-0.817	-0.254	-0.441	-0.195	0.16	0.205	0.436	0.709	0.758
Nestedness	0.719	-0.677	-0.02	0.925	1	-0.729	-0.773	-0.353	-0.434	-0.124	0.084	0.278	0.471	0.751	0.776
Weighted Nestedness	-0.823	0.592	0.367	-0.776	-0.729	1	0.774	0.29	0.279	0.518	0.061	0.251	-0.019	-0.42	-0.659
Weighted NODF	-0.66	0.437	0.292	-0.817	-0.773	0.774	1	0.289	0.532	0.478	0.18	0.131	-0.055	-0.498	-0.7
Interaction Strength Asymmetry	-0.063	0.362	-0.048	-0.254	-0.353	0.29	0.289	1	0.296	0.058	0.154	-0.077	-0.116	-0.273	-0.263
Specialisation Asymmetry	-0.257	0.09	-0.252	-0.441	-0.434	0.279	0.532	0.296	1	0.046	0.117	-0.124	-0.158	-0.261	-0.676
Linkage Density	-0.381	0.032	0.695	-0.195	-0.124	0.518	0.478	0.058	0.046	1	0.661	0.845	0.68	0.171	-0.31
Weighted Connectance	0.218	-0.175	0.333	0.16	0.084	0.061	0.18	0.154	0.117	0.661	1	0.537	0.668	0.286	-0.203
Shannon Diversity	-0.154	-0.202	0.66	0.205	0.278	0.251	0.131	-0.077	-0.124	0.845	0.537	1	0.891	0.536	0.054
Interaction Evenness	0.162	-0.428	0.478	0.436	0.471	-0.019	-0.055	-0.116	-0.158	0.68	0.668	0.891	1	0.7	0.228
Alatalo Interaction Evenness	0.421	-0.592	0.194	0.709	0.751	-0.42	-0.498	-0.273	-0.261	0.171	0.286	0.536	0.7	1	0.448
H2	0.609	-0.523	-0.083	0.758	0.776	-0.659	-0.7	-0.263	-0.676	-0.31	-0.203	0.054	0.228	0.448	1

Table 13. Spearman's correlation matrix for Group-level metrics

	Numbe r of Species HL	Numbe r of Species LL	Mean Number of Links HL	Mean Number of Links LL	Number of Shared Partners HL	Number of Shared Partners LL	Cluster Coefficien t HL	Cluster Coefficien t LL	Weighted Cluster Coefficien t HL	Weighted Cluster Coefficien t LL	Niche Overalp HL	Niche Overlap LL	Togetherne ss HL	Togetherne ss LL	C Score HL	C Score LL	V Ratio HL	V Ratio LL	Discrepanc y HL	Discrepanc y LL	Extinctio n Slope HL	Extinctio n Slope LL	Robustnes s HL	Robustnes s LL	Functional Complementari ty HL	Functional Complementar ity LL	Partner Diversity HL	Partner Diversit y LL	Generalit y HL	Vulnerabilit y LL
Number of Species HL	1	-0.02	-0.506	0.938	-0.551	0.377	-0.579	0.224	0.541	-0.525	0.801	-0.455	0.542	-0.613	-0.921	-0.458	0.682	0.96	0.126	-0.137	-0.554	0.002	-0.622	-0.034	0.213	0.054	-0.132	0.481	0.163	0.422
Number of Species LL	-0.02	1	0.656	-0.077	0.662	-0.574	0.026	-0.379	-0.632	0.636	0.292	-0.733	-0.162	-0.431	-0.177	0.461	-0.335	0.008	0.859	0.868	0.566	-0.28	0.505	-0.182	0.208	0.291	0.697	0.134	0.577	0.202
Mean Number of Links HL	-0.506	0.656	1	-0.608	0.89	-0.253	0.688	-0.55	-0.633	0.931	-0.261	-0.037	-0.315	0.208	0.258	0.33	-0.479	-0.454	0.375	0.727	0.742	-0.06	0.732	0.014	-0.181	-0.003	0.812	0.052	0.571	0.188
Mean Number of Links LL	0.938	-0.077	-0.608	1	-0.558	0.348	-0.698	0.477	0.586	-0.571	0.784	-0.427	0.618	-0.6	-0.835	-0.43	0.612	0.931	0.033	-0.153	-0.531	0.072	-0.578	0.047	0.364	0.206	-0.285	0.433	-0.031	0.37
Mean Number of Shared Partners HL	-0.551	0.662	0.89	-0.558	1	-0.232	0.521	-0.295	-0.513	0.962	-0.167	-0.114	-0.194	0.139	0.29	0.405	-0.648	-0.503	0.373	0.817	0.898	0.157	0.888	0.243	0.008	0.189	0.664	0.04	0.34	0.168
Mean Number of Shared Partners LL	0.377	-0.574	-0.253	0.348	-0.232	1	0.098	0.304	0.821	-0.198	0.178	0.451	0.509	0.262	-0.361	-0.725	0.448	0.325	-0.617	-0.337	-0.221	0.612	-0.229	0.534	-0.126	-0.182	-0.195	0.497	-0.091	0.502
Cluster Coefficient HL	-0.579	0.026	0.688	-0.698	0.521	0.098	1	-0.543	-0.313	0.617	-0.511	0.517	-0.334	0.519	0.473	0.198	-0.471	-0.594	-0.109	0.252	0.46	0.152	0.477	0.197	-0.394	-0.248	0.523	-0.168	0.352	-0.042
Cluster Coefficient LL	0.224	-0.379	-0.55	0.477	-0.295	0.304	-0.543	1	0.588	-0.375	0.211	0.087	0.612	-0.179	-0.138	-0.199	0.181	0.301	-0.356	-0.265	-0.236	0.239	-0.224	0.179	0.197	0.127	-0.632	0.166	-0.62	0.092
Cluster Coefficient HL	0.541	-0.632	-0.633	0.586	-0.513	0.821	-0.313	0.588	1	-0.524	0.331	0.221	0.591	-0.075	-0.445	-0.598	0.528	0.486	-0.526	-0.496	-0.434	0.482	-0.482	0.414	0.009	-0.122	-0.526	0.364	-0.357	0.293
Cluster Coefficient LL	-0.525	0.636	0.931	-0.571	0.962	-0.198	0.617	-0.375	-0.524	1	-0.189	-0.036	-0.2	0.143	0.286	0.38	-0.625	-0.489	0.366	0.778	0.865	0.146	0.857	0.226	-0.097	0.09	0.749	0.055	0.453	0.199
HL	0.801	0.292	-0.261	0.784	-0.167	0.178	-0.511	0.211	0.331	-0.189	1	-0.638	0.497	-0.702	-0.787	-0.11	0.273	0.762	0.364	0.239	-0.197	0.099	-0.26	0.107	0.407	0.309	0.063	0.345	0.218	0.339
LL	-0.455	-0.733	-0.037	-0.427	-0.114	0.451	0.517	0.087	0.221	-0.036	-0.638	1	-0.113	0.746	0.529	-0.237	-0.049	-0.448	-0.768	-0.521	-0.046	0.359	0.043	0.301	-0.447	-0.399	-0.233	-0.176	-0.287	-0.158
HL	0.542	-0.162	-0.315	0.618	-0.194	0.509	-0.334	0.612	0.591	-0.2	0.497	-0.113	1	-0.422	-0.579	-0.223	0.202	0.607	-0.142	0.018	-0.249	0.246	-0.249	0.201	0.336	0.293	-0.146	0.51	-0.074	0.526
LL	-0.613	-0.431	0.208	-0.6	0.139	0.262	0.519	-0.179	-0.075	0.143	-0.702	0.746	-0.422	1	0.629	-0.324	-0.021	-0.612	-0.653	-0.337	0.154	0.201	0.244	0.163	-0.344	-0.288	-0.056	-0.064	-0.137	-0.041
C Score HL	-0.921	-0.177	0.258	-0.835	0.29	-0.361	0.473	-0.138	-0.445	0.286	-0.787	0.529	-0.579	0.629	1	0.377	-0.595	-0.912	-0.237	-0.104	0.351	-0.037	0.429	-0.008	-0.263	-0.146	-0.085	-0.573	-0.31	-0.551
C Score LL	-0.458	0.461	0.33	-0.43	0.405	-0.725	0.198	-0.199	-0.598	0.38	-0.11	-0.237	-0.223	-0.324	0.377	1	-0.796	-0.415	0.593	0.465	0.363	-0.159	0.369	-0.083	0.143	0.265	0.248	-0.556	0.031	-0.513
V Ratio HL	0.682	-0.335	-0.479	0.612	-0.648	0.448	-0.471	0.181	0.528	-0.625	0.273	-0.049	0.202	-0.021	-0.595	-0.796	1	0.686	-0.307	-0.543	-0.657	-0.159	-0.697	-0.253	-0.171	-0.344	-0.305	0.503	0.025	0.399
V Ratio LL	0.96	0.008	-0.454	0.931	-0.503	0.325	-0.594	0.301	0.486	-0.489	0.762	-0.448	0.607	-0.612	-0.912	-0.415	0.686	1	0.106	-0.098	-0.563	-0.062	-0.614	-0.103	0.199	0.061	-0.132	0.512	0.139	0.458
Discrepancy HL	0.126	0.859	0.375	0.033	0.373	-0.617	-0.109	-0.356	-0.526	0.366	0.364	-0.768	-0.142	-0.653	-0.237	0.593	-0.307	0.106	1	0.694	0.322	-0.307	0.247	-0.226	0.143	0.186	0.515	-0.009	0.464	0.005
Discrepancy LL	-0.137	0.868	0.727	-0.153	0.817	-0.337	0.252	-0.265	-0.496	0.778	0.239	-0.521	0.018	-0.337	-0.104	0.465	-0.543	-0.098	0.694	1	0.733	-0.009	0.685	0.087	0.214	0.35	0.714	0.138	0.494	0.256
Extinction Slope HL	-0.554	0.566	0.742	-0.531	0.898	-0.221	0.46	-0.236	-0.434	0.865	-0.197	-0.046	-0.249	0.154	0.351	0.363	-0.657	-0.563	0.322	0.733	1	0.23	0.981	0.322	-0.061	0.097	0.556	0.009	0.238	0.113
Extinction Slope LL	0.002	-0.28	-0.06	0.072	0.157	0.612	0.152	0.239	0.482	0.146	0.099	0.359	0.246	0.201	-0.037	-0.159	-0.159	-0.062	-0.307	-0.009	0.23	1	0.232	0.953	0.095	0.133	-0.118	0.081	-0.211	0.124
Robustness HL	-0.622	0.505	0.732	-0.578	0.888	-0.229	0.477	-0.224	-0.482	0.857	-0.26	0.043	-0.249	0.244	0.429	0.369	-0.697	-0.614	0.247	0.685	0.981	0.232	1	0.321	-0.029	0.139	0.529	-0.04	0.193	0.074
Robustness LL	-0.034	-0.182	0.014	0.047	0.243	0.534	0.197	0.179	0.414	0.226	0.107	0.301	0.201	0.163	-0.008	-0.083	-0.253	-0.103	-0.226	0.087	0.322	0.953	0.321	1	0.192	0.238	-0.061	0.023	-0.19	0.093
Functional Complementari ty HL	0.213	0.208	-0.181	0.364	0.008	-0.126	-0.394	0.197	0.009	-0.097	0.407	-0.447	0.336	-0.344	-0.263	0.143	-0.171	0.199	0.143	0.214	-0.061	0.095	-0.029	0.192	1	0.97	-0.066	-0.09	-0.089	-0.035
Functional Complementari ty LL	0.054	0.291	-0.003	0.206	0.189	-0.182	-0.248	0.127	-0.122	0.09	0.309	-0.399	0.293	-0.288	-0.146	0.265	-0.344	0.061	0.186	0.35	0.097	0.133	0.139	0.238	0.97	1	0.054	-0.122	-0.046	-0.04
Partner Diversity HL	-0.132	0.697	0.812	-0.285	0.664	-0.195	0.523	-0.632	-0.526	0.749	0.063	-0.233	-0.146	-0.056	-0.085	0.248	-0.305	-0.132	0.515	0.714	0.556	-0.118	0.529	-0.061	-0.066	0.054	1	0.287	0.893	0.41
Partner Diversity LL	0.481	0.134	0.052	0.433	0.04	0.497	-0.168	0.166	0.364	0.055	0.345	-0.176	0.51	-0.064	-0.573	-0.556	0.503	0.512	-0.009	0.138	0.009	0.081	-0.04	0.023	-0.09	-0.122	0.287	1	0.405	0.967
Generality HL	0.163	0.577	0.571	-0.031	0.34	-0.091	0.352	-0.62	-0.357	0.453	0.218	-0.287	-0.074	-0.137	-0.31	0.031	0.025	0.139	0.464	0.494	0.238	-0.211	0.193	-0.19	-0.089	-0.046	0.893	0.405	1	0.502
Vulnerability LL	0.422	0.202	0.188	0.37	0.168	0.502	-0.042	0.092	0.293	0.199	0.339	-0.158	0.526	-0.041	-0.551	-0.513	0.399	0.458	0.005	0.256	0.113	0.124	0.074	0.093	-0.035	-0.04	0.41	0.967	0.502	1

Table 14. Spearman's correlation matrix for Species-level metrics

	Degree	Normalised Degree	Species Strength	Interaction Push Pull	Nested Rank	PDI	Resource Range	Species Specificity Index	PSI	NSI	Betweenness	Weighted Betweenness	Closeness	Weighted Closeness	Fisher Alpha	Partner Diversity	Effective Partners	Proportional Generality	Proportional Similarity	d'
Degree	1	0.93	0.821	0.871	-0.834	-0.753	-0.946	-0.829	-0.33	-0.681	0.457	0.434	0.594	0.592	NA	0.894	0.894	0.817	0.675	-0.155
Normalised Degree	0.93	1	0.738	0.805	-0.868	-0.808	-0.992	-0.83	-0.093	-0.564	0.551	0.485	0.434	0.527	NA	0.871	0.871	0.772	0.634	-0.159
Species Strength	0.821	0.738	1	0.977	-0.687	-0.579	-0.753	-0.661	-0.322	-0.541	0.203	0.48	0.586	0.725	NA	0.731	0.731	0.722	0.49	0.197
Interaction Push Pull	0.871	0.805	0.977	1	-0.737	-0.66	-0.818	-0.73	-0.326	-0.599	0.287	0.469	0.616	0.708	NA	0.794	0.794	0.774	0.535	0.132
Nested Rank	-0.834	-0.868	-0.687	-0.737	1	0.662	0.862	0.705	-0.037	0.411	-0.51	-0.519	-0.261	-0.404	NA	-0.744	-0.744	-0.625	-0.464	0.076
PDI	-0.753	-0.808	-0.579	-0.66	0.662	1	0.813	0.973	0.19	0.559	-0.581	-0.41	-0.455	-0.475	NA	-0.934	-0.934	-0.851	-0.698	0.294
Resource Range	-0.946	-0.992	-0.753	-0.818	0.862	0.813	1	0.841	0.133	0.587	-0.549	-0.481	-0.458	-0.547	NA	-0.884	-0.884	-0.784	-0.658	0.167
Species Specificity Index	-0.829	-0.83	-0.661	-0.73	0.705	0.973	0.841	1	0.283	0.622	-0.549	-0.426	-0.525	-0.523	NA	-0.981	-0.981	-0.905	-0.719	0.276
PSI	-0.33	-0.093	-0.322	-0.326	-0.037	0.19	0.133	0.283	1	0.686	-0.08	-0.043	-0.783	-0.441	NA	-0.316	-0.316	-0.493	-0.534	0.263
NSI	-0.681	-0.564	-0.541	-0.599	0.411	0.559	0.587	0.622	0.686	1	-0.501	-0.343	-0.831	-0.622	NA	-0.645	-0.645	-0.673	-0.714	0.277
Betweenness	0.457	0.551	0.203	0.287	-0.51	-0.581	-0.549	-0.549	-0.08	-0.501	1	0.364	0.223	0.217	NA	0.513	0.513	0.455	0.507	-0.361
Weighted Betweenness	0.434	0.485	0.48	0.469	-0.519	-0.41	-0.481	-0.426	-0.043	-0.343	0.364	1	0.221	0.525	NA	0.422	0.422	0.349	0.472	-0.125
Closeness	0.594	0.434	0.586	0.616	-0.261	-0.455	-0.458	-0.525	-0.783	-0.831	0.223	0.221	1	0.573	NA	0.554	0.554	0.693	0.612	-0.144
Weighted Closeness	0.592	0.527	0.725	0.708	-0.404	-0.475	-0.547	-0.523	-0.441	-0.622	0.217	0.525	0.573	1	NA	0.551	0.551	0.536	0.675	-0.113
Fisher Alpha	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1	NA	NA	NA	NA	NA
Partner Diversity	0.894	0.871	0.731	0.794	-0.744	-0.934	-0.884	-0.981	-0.316	-0.645	0.513	0.422	0.554	0.551	NA	1	1	0.92	0.716	-0.236
Effective Partners	0.894	0.871	0.731	0.794	-0.744	-0.934	-0.884	-0.981	-0.316	-0.645	0.513	0.422	0.554	0.551	NA	1	1	0.92	0.716	-0.236
Proportional Generality	0.817	0.772	0.722	0.774	-0.625	-0.851	-0.784	-0.905	-0.493	-0.673	0.455	0.349	0.693	0.536	NA	0.92	0.92	1	0.708	-0.179
Proportional Similarity	0.675	0.634	0.49	0.535	-0.464	-0.698	-0.658	-0.719	-0.534	-0.714	0.507	0.472	0.612	0.675	NA	0.716	0.716	0.708	1	-0.609
d'	-0.155	-0.159	0.197	0.132	0.076	0.294	0.167	0.276	0.263	0.277	-0.361	-0.125	-0.144	-0.113	NA	-0.236	-0.236	-0.179	-0.609	1